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from Bayesian Proxy SVARs**

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Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs

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Abstract

This paper studies the interaction between monetary policy, financial markets, and the real economy. We develop a Bayesian framework to estimate proxy structural vector autoregressions (SVARs) in which monetary policy shocks are identified by exploiting the information contained in high frequency data. For the Great Moderation period, we find that monetary policy shocks are key drivers of fluctuations in industrial output and corporate credit spreads, explaining about 20 percent of the volatility of these variables. Central to this result is a systematic component of monetary policy characterized by a direct and economically significant reaction to changes in credit spreads. We show that the failure to account for this endogenous reaction induces an attenuation bias in the response of all variables to monetary shocks.

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1 Introduction

Starting with [Sims \(1980\)](#), a long literature has assessed the effects of monetary policy using structural vector autoregressions (SVARs). Many papers have found that identified monetary tightenings reduce output.¹ However, the issue is far from settled, with [Uhlig \(2005\)](#) notably finding that monetary policy has no real effects, and more recent studies finding that the effects of monetary policy on the real economy have become muted over time, in particular during the Great Moderation period.² Furthermore, the consensus in the literature is that shocks to monetary policy do not significantly contribute to business cycle fluctuations.

This paper provides new evidence on the importance of monetary policy for business cycle fluctuations for the 1994–2007 period. We identify monetary policy shocks by estimating a Bayesian proxy SVAR (BP-SVAR) that exploits information contained in monetary surprises computed using high-frequency data. We find that positive monetary policy shocks induce a sustained decline in real economic activity and are accompanied by a significant tightening in financial conditions. Moreover, at the posterior mean of our preferred VAR specification, monetary shocks explain about 20 percent of the volatility of industrial output and corporate credit spreads at business cycle frequencies, a contribution about four times larger than standard estimates.

Arriving at this conclusion requires explicitly acknowledging the two-way interaction between measures of corporate credit spreads and monetary policy. On the one hand, several recent papers have concentrated on assessing the transmission of monetary policy through financial markets, both empirically ([Gertler and Karadi, 2015](#); [Galí and Gambetti, 2015](#)) and theoretically.³ On the other hand, [Rigobon and Sack \(2003\)](#) have provided evidence that monetary policy endogenously reacts to changes in asset prices. Hence, the endogeneity of monetary policy to financial variables and the reaction of asset prices to monetary policy present a clear identification problem. We document that both channels are quantitatively important. In our BP-SVAR, monetary policy shocks are transmitted through tightening in financial conditions and, at the same time, monetary policy displays a large and significant response to changes in corporate credit spreads: All else being equal, a 20 basis point increase in spreads leads to a 10 basis point drop in the federal funds rate at our posterior mean estimate. An implication of the systematic response of monetary policy to financial conditions is that the effects of shocks which originate in or transmit through financial markets—for example, [Gilchrist and Zakrajsek \(2012\)](#)—are substantially smaller in comparison to standard estimates.

Our analysis shows that the failure to account for the endogenous response of monetary policy to corporate credit spreads induces an attenuation bias in the estimated response of real activity to monetary policy shocks.

In misspecified models that omit the endogenous response of monetary policy to credit spreads, a monetary

¹See [Bernanke and Blinder \(1992\)](#); [Christiano, Eichenbaum, and Evans \(1996\)](#); [Leeper, Sims, and Zha \(1996\)](#); [Leeper and Zha \(2003\)](#); [Romer and Romer \(2004\)](#); and, more recently, [Arias, Caldara, and Rubio-Ramírez \(2015\)](#).

²See [Hanson \(2004\)](#); [Boivin and Giannoni \(2006\)](#); [Boivin, Kiley, and Mishkin \(2010\)](#); and [Castelnuovo and Surico \(2010\)](#).

³Dynamic stochastic general equilibrium models with financial frictions have been pioneered by [Bernanke, Gertler, and Gilchrist \(1999\)](#). [Gertler and Karadi \(2011\)](#) provide a recent application to study the transmission of monetary policy.

shock is a mix of truly exogenous changes in policy and negative changes in credit spreads (as the elasticity of the fed funds rate to spreads is negative). The bias toward zero happens because a drop in credit spreads generates a persistent increase in real activity.

To quantify the effect of this kind of misspecification, we estimate two variants of the model. In particular, we find that monetary shocks identified in a BP-SVAR that omits credit spreads induce no change in industrial production. We also show that monetary shocks identified by imposing that the fed funds rate does not react contemporaneously to changes in credit spreads (a standard Cholesky identification) induce a decline in industrial production that is 40 percent smaller than in our preferred BP-SVAR specification. This result explains why our findings differ from the conventional wisdom that monetary policy does not contribute much to business cycle fluctuations.

Our paper also provides a methodological contribution to the recent literature on proxy SVARs. We provide an encompassing framework that jointly models the interaction between the SVAR and the proxy. In particular, we write the likelihood of a SVAR model augmented with a measurement equation that relates the proxy to the unobserved structural shock and estimate the model using Bayesian techniques. A first advantage over the standard framework is that inference is valid regardless of the information content of the proxy for the structural shock, requiring no modification for so-called weak instruments, as long as a proper prior is specified. A second advantage is that, as we coherently incorporate all sources of uncertainty in the estimation, the proxy becomes informative about both the reduced-form and structural parameters of the model. A third advantage is that, through prior distributions, we can adjust the informativeness of the proxy for the estimation of the parameters of the SVAR model.⁴ That is, researchers that are convinced of the quality of their proxies can enforce their priors and induce the estimation to take a lot of signal from them. In particular, following [Mertens and Ravn \(2013\)](#), we impose priors on the “reliability” of the proxy, defined as the correlation between the structural shocks identified in the SVAR and the proxies used to identify them.⁵

Our analysis exploits the Bayesian framework to gain new insights on proxy SVARs by estimating models for different priors on the degree of reliability. In our applications, we find that shrinking the prior toward a relevant proxy—that is, imposing a high reliability of the proxy—can substantially reduce noise and sharpen inference but only if the VAR contains observables that reflect the key transmission mechanisms of monetary policy. By contrast, we show that VAR misspecification in the form of omitted variables introduces endogeneity that can severely bias the dynamic response of the endogenous variables to the shock of interest, regardless of the reliability of the proxy. Moreover, we find that detecting model misspecification is extremely

⁴This feature is one major differentiation of our analysis from other Bayesian approaches: for example, [Bahaj \(2014\)](#) and [Drantberg \(2015\)](#).

⁵The reliability index is defined as $(\text{signal})/(\text{signal}+\text{noise})$ and hence is similar to the signal-to-noise ratio in the measurement equation.

hard, as models with different implications can have an identical degree of reliability.

Intuitively, proxy SVARs identify structural shocks by instrumenting the endogenous reduced-form VAR residuals with exogenous proxies for the unobserved structural shocks. A high degree of reliability mostly signals that the proxy can be a good instrument in these IV-type regressions, and that we can obtain reliable estimates of the *contemporaneous* response of the endogenous variables to the structural shock. However, the reliability indicator is silent about the possibility of missing key variables in the system that could alter the *dynamic* responses of *all* variables to the shock. This is why, even with a well-constructed and reliable proxy, if the VAR is misspecified, the BP-SVAR will provide misleading inference. Hence the argument of [Romer and Romer \(2010\)](#), that observing a carefully constructed proxy closely related to the policy shock yields an unbiased estimate even in the presence of omitted variables, does not apply to this methodology.

Our methodological results have important implications for the existing literature on proxy SVARs. The result that the specification of the VAR model is consequential for inference, irrespective of the quality of the proxy, is important because most of the literature focuses on the relevance and exogeneity of the proxy rather than the specification of the VAR model. Consequently, the importance of model misspecification and the impossibility of correcting it through the priors motivates the estimation of large systems, and the Bayesian framework is particularly well-suited to this task.

The starting point of our analysis is [Gertler and Karadi \(2015\)](#), who also employ a monetary proxy SVAR that includes financial variables. Indeed, we document similar responses of real activity and corporate credit spreads to monetary policy shocks. However, relative to [Gertler and Karadi \(2015\)](#), we show that the addition of corporate credit spreads to the proxy SVAR leads to a dramatic difference in the response of *all* model variables to the monetary shock and, in terms of forecast error variance, makes such monetary shocks important drivers of the cycle. In addition, we characterize the endogenous component of monetary policy and show that although it reacts contemporaneously to corporate credit spreads and stock returns, it does not react contemporaneously to prices, several measures of real activity, or mortgage spreads. Finally, we provide a Bayesian framework for inference and derive implications for the literature on proxy SVARs that extend beyond our application to monetary policy.

In our empirical analysis, we use the proxies for monetary policy shocks constructed from high-frequency data around Federal Open Market Committee (FOMC) statements. Price changes in federal funds rate futures during a narrow window around FOMC statements provide a measure of the unexpected component of monetary policy, which we aggregate to a monthly frequency. Our paper follows the literature, pioneered by [Kuttner \(2001\)](#), that uses event studies to examine monetary policy shocks. Other influential studies include [Bernanke and Kuttner \(2005\)](#); [Gürkaynak, Sack, and Swanson \(2005\)](#); [Campbell, Evans, Fisher, and Justiniano \(2012\)](#); and [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#). The bulk of these studies consider

simple univariate regressions for assessing the effects on monetary policy on daily changes in asset prices. In contrast, we are more concerned with studying the interaction between monetary policy, and macroeconomic and financial conditions. Therefore, we use a VAR as our principal framework for analysis.⁶

The paper is structured as follows. Section 2 describes the BP-SVAR model and the estimation procedure. Section 3 describes the data. Section 4 shows the main empirical findings based on small proxy SVARs. Section 5 documents how identification and inference depend on the informativeness of the proxy. Section 6 extends the analysis to larger models. Section 7 explores robustness to alternative measures of corporate credit spreads. Section 8 concludes.

2 Econometric Methodology

In this section, we first describe a standard SVAR model and illustrate the identification problem from a Bayesian perspective. We then present the BP-SVAR, the prior distributions, and the sampler used to draw from the posterior distribution. Finally, we discuss some key properties of the model and the model's relationship with the literature.

2.1 The SVAR Model

Consider the following VAR, written in structural form:

$$y'_t A_0 = \sum_{\ell=1}^p y'_{t-\ell} A_\ell + c + e'_t, \quad \text{for } 1 \leq t \leq T, \quad (1)$$

where y_t is an $n \times 1$ vector of endogenous variables, e_t is an $n \times 1$ vector of structural shocks, A_ℓ is an $n \times n$ matrix of structural parameters for $0 \leq \ell \leq p$ with A_0 invertible, c is a $1 \times n$ vector of parameters, p is the lag length, and T is the sample size. The vector e_t , conditional on past information and the initial conditions y_0, \dots, y_{1-p} , is Gaussian with a mean of zero and covariance matrix I_n (the $n \times n$ identity matrix). The model described in Equation (1) can be written as

$$y'_t A_0 = x'_t A_+ + e'_t, \quad \text{for } 1 \leq t \leq T, \quad (2)$$

where $x_t = [y'_{t-1}, \dots, y'_{t-p}, 1]'$ and $A_+ = [A'_1, \dots, A'_p, c]'$. The reduced-form representation of this model is given by

$$y'_t = x'_t \Phi + u'_t, \quad u_t \sim \mathcal{N}(0, \Sigma). \quad (3)$$

⁶In an early work, Faust, Swanson, and Wright (2004) use the responses of federal funds rate futures contracts to FOMC announcements to identify a VAR but omit measures of financial conditions.

The reduced-form parameters and the structural parameters are linked through

$$\Sigma = (A_0 A_0')^{-1} \text{ and } \Phi = A_+ A_0^{-1}. \quad (4)$$

When the object of interest is, say, assessing the effects of shocks e_t on observables or decomposing the structural sources of fluctuations, the econometrician requires knowledge of (potentially a subset of) the parameters (A_0, A_+) . As is well known, without additional restrictions, it is not possible to obtain unique estimates of the structural parameters given the reduced-form parameters. This is because it is impossible to discriminate between the many possible combinations of structural shocks that yield the same reduced-form residuals, u_t ; that is, the likelihood is flat with respect to these combinations. To see this, let Σ_{tr} be the lower-triangular Cholesky factorization of Σ and let $\Omega \in \mathcal{O}(n)$, where $\mathcal{O}(n)$ is the space of all orthogonal matrices of size $n \times n$, so that

$$A_0 = \Sigma_{tr}^{-1'} \Omega. \quad (5)$$

It can be verified that any two orthogonal matrices Ω and $\tilde{\Omega} \in \mathcal{O}(n)$ yield two sets of structural coefficients A_0 and \tilde{A}_0 that give rise to identical likelihoods. The majority of the literature, beginning with [Sims \(1980\)](#), has used theoretical restrictions to achieve identification—that is, to inform choices of Ω . The Bayesian framework incorporates the information from theoretical restrictions in the form of a distribution over Ω , denoted by $p(\Omega)$. To see how the data and the restrictions imposed on Ω interact, we can decompose the joint distribution of data and parameters as follows:⁷

$$p(Y_{1:T}, \Phi, \Sigma, \Omega) = p(Y_{1:T} | \Phi, \Sigma) p(\Phi, \Sigma) p(\Omega). \quad (6)$$

The first density on the right-hand side of Equation (6) is the likelihood function for $Y_{1:T}$, which does not depend on Ω . A direct implication is that the distribution for Ω is not updated in light of the data:

$$p(\Omega | Y_{1:T}) = p(\Omega). \quad (7)$$

Because the data do not contain information on $p(\Omega)$, most debates in the SVAR literature are about the “correct” choice of distribution for any given application. For instance, in many cases, $p(\Omega)$ is dogmatic in the sense that it implies probability one to a single Ω . A common dogmatic identification scheme is to set

⁷We use the notation $Y_{1:T}$ for $[y_1 \dots y_T]'$. In this and what follows, we suppress any dependence on the initial conditions $Y_{-p:0}$ for convenience.

$\Omega = I_n$, which corresponds to the widely used Cholesky factorization of Σ .⁸

2.2 The Bayesian Proxy SVAR

In this paper, we follow a different strategy and inform the choice of Ω by incorporating additional data, the proxies, that contain information about a subset of the structural shocks in the SVAR. Proxies are typically constructed using event studies, microdata, or high-frequency data, and hence contain information about the structure of the model coming from sources of variation that are external to the SVAR. Key to our methodology is to use a probability distribution that does not rule out any Ω *a priori* and incorporate the proxy in the SVAR so that prior beliefs $p(\Omega)$ are updated by the proxy in a probabilistic way.⁹

In what follows, we take the proxy, m_t , to be an observation from a scalar-valued time series of length T . We link m_t to a particular structural shock of interest that, without loss of generality, we assume is the first shock $e_{1,t}$. The relationship between m_t and $e_{1,t}$ is given by

$$m_t = \beta e_{1,t} + \sigma_\nu \nu_t, \quad \nu_t \sim \mathcal{N}(0, 1) \text{ and } \nu_t \perp e_t. \quad (8)$$

The formulation in Equation (8) has two implications. The first is that the squared correlation between m_t and $e_{1,t}$,

$$\rho \equiv CORR(m_t, e_{1,t})^2 = \frac{\beta^2}{\beta^2 + \sigma_\nu^2}, \quad (9)$$

measures the “relevance” of the external information for the structural shock of interest. [Mertens and Ravn \(2013\)](#) call ρ the reliability indicator for the proxy. Equation (8) makes clear that the reliability indicator is directly related to the signal-to-noise ratio β/σ . The larger this value, the more information the proxy brings to bear on the identification of the SVAR. The second implication of Equation (8) is that m_t is orthogonal to other structural shocks in the VAR, $e_{/1,t}$:

$$E[m_t e_{/1,t}] = 0. \quad (10)$$

Equation (10) conveys the exogeneity of the proxy. This condition ensures that our proxy is only informative about a single shock or, equivalently, a single column of Ω . These two conditions are very similar to those

⁸More generally, researchers allow for this distribution to depend on the reduced-form parameters, writing this prior as $p(\Omega|\Phi, \Sigma)$. Many common prior distributions—ones based on sign restrictions, for example—exhibit this dependence. As in our framework, $p(\Omega)$ does not depend on (Φ, Σ) , we suppress this dependence for notational convenience. [Del Negro and Schorfheide \(2011\)](#) survey how many common identification schemes map into assumption on Ω .

⁹The framework is a Bayesian implementation of the proxy SVAR approach of [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#). The proxy structural VAR approach has been motivated as an instrumental variable approach for the reduced-form residuals, but [Mertens and Ravn \(2013\)](#) show that, under some restrictions, it is equivalent to a model in which the proxy is simply a linear function of the structural shock of interest subject to measurement error.

required of an instrument in an instrumental variables regression. The setting, however, is different: In practice, what matters is the relationship between m_t and u_t , the unobserved structural shock from the SVAR.

To examine in detail how the proxy interacts with the rest of the structural VAR, we augment Equation (1) with Equation (8). Letting $\tilde{y}_t = [y'_t, m_t]'$, $\tilde{e}_t = [e'_t, \nu_t]'$, and similarly defining \tilde{x}_t , we can rewrite Equation (1) as a system of equations for \tilde{y}_t :

$$\tilde{y}'_t \tilde{A}_0 = \tilde{x}'_t \tilde{A}_+ + \tilde{e}'_t. \quad (11)$$

The structural matrices \tilde{A}_0 and \tilde{A}_+ are functions of the original structural VAR matrices, (A_0, A_+) , and the parameters governing the proxy equation, (β, σ_ν) , with

$$\tilde{A}_0 = \begin{bmatrix} A_0 & -\frac{\beta}{\sigma} A_{.1,0} \\ O_{1 \times n} & \frac{1}{\sigma} \end{bmatrix}, \text{ and } \tilde{A}_+ = \begin{bmatrix} A_+ & -\frac{\beta}{\sigma} A_{.1,+} \\ O_{1 \times n} & 0 \end{bmatrix}. \quad (12)$$

As can be seen from Equation (12), the proxy SVAR is an augmented SVAR that links the proxy to the structural shock of interest through the structural coefficients associated with it.

2.3 Understanding Identification in BP-SVARs

To understand how identification works in BP-SVARs, it is instructive to write the joint likelihood function for $Y_{1:T}$ and $M_{1:T}$:

$$p(Y_{1:T}, M_{1:T} | \Phi, \Sigma, \Omega, \beta, \sigma_\nu) = p(Y_{1:T} | \Phi, \Sigma) p(M_{1:T} | Y_{1:T}, \Phi, \Sigma, \Omega, \beta, \sigma_\nu). \quad (13)$$

The first term on the right-hand side of Equation (13) is the likelihood of the VAR data $Y_{1:T}$. This likelihood contains information only about the reduced-form parameters Φ and Σ . The second term, which is unique to BP-SVARs, is the conditional likelihood of the proxy $M_{1:T}$ given the VAR data $Y_{1:T}$, which has the following closed-form solution:¹⁰

$$M_{1:T} | Y_{1:T}, \Phi, \Sigma, \beta, \sigma_\nu \sim \mathcal{N}(\mu_{M|Y}, V_{M|Y}),$$

with

$$\mu_{M|Y} = [\beta \Omega'_{.1} \Sigma_{tr}^{-1} (Y_{1:T} - X_{1:T} \Phi)]' \quad \text{and} \quad V_{M|Y} = \sigma_\nu^2 I_T, \quad (14)$$

where $\mu_{M|Y}$ and $V_{M|Y}$ are the mean and variance, respectively, associated with the normally distributed likelihood. Because the conditional likelihood of the proxy $M_{1:T}$ given $Y_{1:T}$ is a function of all parameters of

¹⁰See the Appendix for the derivations.

the proxy SVAR all prior distributions, including $p(\Omega)$, are updated in light of the information contained in the proxy. As we see from the expression for $\mu_{M|Y}$, for given values of Φ , Σ , β , and σ_ν , the econometrician updates the beliefs about the identification of the structural shock e_1 by giving relatively more weight to Ω s, which results in linear combinations of “standardized residuals” ($\Sigma_{tr}^{-1}u_t$) that look like a scaled version of the proxy. Similarly, for given values of Ω , β , and σ_ν , the econometrician updates the beliefs about the reduced-form coefficients Ψ and Σ by giving relatively more weight to the reduced-form residuals that span the proxy m_t . This coherent modeling of all sources of uncertainty through the joint likelihood, and, hence, the ability to exploit the information content of the proxy to estimate both reduced-form and structural parameters of the BP-SVAR, constitutes a first advantage of our framework over traditional proxy SVAR models.

The expressions for $\mu_{M|Y}$ and $V_{M|Y}$ reported in Equation (14), as well as the expressions for the structural matrices described by Equation (12), also reveal that the signal-to-noise ratio β/σ is crucial for identifying the coefficients of the SVAR. When β/σ is large, m_t provides a lot of information about $e_{1,t}$ and, consequently, about the structural parameters $A_{1,0}$ (or, equivalently, about $\Omega'_{1,1}\Sigma_{tr}^{-1}(Y_{1:T} - X_{1:T}\Phi)'$). However, when $\beta = 0$, m_t is simply noise and provides no information about $A_{1,0}$. Finally, when β/σ is close to zero, but not zero, we have weak identification.

A second advantage of the BP-SVAR over standard proxy SVARs estimated using a frequentist approach is that in a Bayesian setting, weak identification does not pose a problem per se—as long as the prior distribution is proper, inference is possible.¹¹ Although a comprehensive analysis of this issue is outside the scope of this paper, it is important to highlight that in the case of weak identification, the prior plays an important role in inference. But in our framework, comparing prior to posterior distributions, a standard diagnostic check to detect weak identification is trivial. The reason is that, as already shown by Equation (13), when it comes to identification, the relevant prior distributions are those implied by the model before observing $M_{1:T}$ but after observing $Y_{1:T}$, as the VAR data are not informative about Ω . Drawing from this prior is easy and is achieved by combining draws from $\Phi, \Sigma|Y_{1:T}$ with draws from the prior from Ω .

A third advantage over the standard framework is that, through prior distributions, we can adjust the informativeness of the proxy for the estimation of the parameters of the BP-SVAR model. In practice, researchers construct proxies to be relevant—that is, to contain a lot of information about the structural shock of interest. This effort is consistent with a prior view of a high degree of reliability ρ , or, equivalently, of a high signal-to-noise ratio β/σ . We operationalize this kind of prior, along with more diffuse ones, by constructing prior distributions where ν can only explain a fraction of the variation in $M_{1:T}$.¹²

This kind of prior shrinkage is not a panacea, though. In sections 4 and 5, we show that shrinking the prior

¹¹See, for instance, Poirier (1998). Of course, lack of identification or weak identification, which manifests itself as flat or nearly flat likelihood profiles, could pose practical issues when sampling the posterior.

¹²There are many ways of doing this. One could use a change of variables and parameterize ρ directly, for instance.

toward a relevant proxy—that is, imposing a high reliability of the proxy—can substantially reduce noise and sharpen inference but only if the VAR contains observables that reflect the key transmission mechanisms for the shock of interest. By contrast, we show that VAR misspecification in the form of omitted variables introduces endogeneity that can severely bias inference, regardless of the reliability of the proxy. Moreover, we find that detecting model misspecification is extremely hard, as models with different implications can have an identical degree of reliability.

The analytical expression for $\mu_{M|Y}$ can help shed light on these features of proxy SVARs. The reliability of the proxy is determined by its *contemporaneous* relationship with the reduced-form residuals of the endogenous variables *included in the model*. Hence, a proxy can be highly reliable because it contains information about the impact responses of some variables. But in most applications—including the application to monetary policy presented in this paper—researchers are interested in the dynamic responses, as the effects of many macroeconomic shocks occur only after a substantial delay. The dynamic propagation of the (correctly estimated) impact responses uniquely depends on the specification of the VAR model and is mostly unrelated to the reliability of the proxy. In fact, although in principle misspecified dynamics could be reflected in the estimation of u_t and hence be reflected in the reliability of the proxy, in practice we find that the impact on misspecification on the reliability indicator is extremely modest. Although it is true that variable omission can affect inference in a large class of models (Sims, 1992), and not just in proxy VARs, we think it is worth underscoring this feature of proxy SVARs, as the literature has placed a large emphasis on the proxy and not on the specification of the VAR model.

2.4 Prior Distributions and Posterior Sampler

Prior Distributions. We assume independent prior distributions for (Φ, Σ) , Ω , and (β, σ_ν) , so we can factorize the joint distribution as

$$p(\Phi, \Sigma, \Omega, \beta, \sigma_\nu) = p(\Phi, \Sigma)p(\Omega)p(\beta, \sigma_\nu).$$

The advantage of working with independent priors is that we have more flexibility to select prior distributions for the different blocks of the parameter space, which we discuss next.

The prior on the reduced-form parameters $p(\Phi, \Sigma)$ is parameterized so that the prior is conjugate to the likelihood $p(Y_{1:T}|\Phi, \Sigma)$. The implication is that the posterior conditional on the VAR data $Y_{1:T}$ is known in closed-form. For densely parameterized models, statistical shrinkage is necessary, so we use a Minnesota Prior, which has a multivariate normal-inverse Wishart form. Specifically, we use the dummy observation implementation of the Minnesota Prior discussed in Del Negro and Schorfheide (2011).

Key to our approach is to choose a prior for Ω that is easy to sample from and that ensures a good

coverage of $\mathcal{O}(n)$, the set of all orthonormal matrices. To this end, we use the uniform prior discussed in Rubio-Ramírez, Waggoner, and Zha (2010). This prior can be sampled from by drawing an $n \times n$ matrix where each element is an independent random normal draw. The QR factorization of this matrix, with R having positive diagonal elements, gives Ω .¹³

The prior for β and σ_ν can be chosen to be conjugate to the likelihood function. In what follows, we maintain a general prior $p(\beta, \sigma_\nu)$ and do not exploit conjugacy to give us the flexibility to shrink the prior $p(\beta, \sigma_\nu)$ to impose a higher signal-to-noise ratio. We choose the following distributions:

$$p(\beta) \sim \mathcal{N}(\mu_\beta, \sigma_\beta), \quad (15)$$

$$p(\sigma_\nu) \sim \mathcal{U}[0, \bar{\sigma}_\nu \text{std}(M_{1:T})]. \quad (16)$$

The standard deviation of the measurement error σ_ν is uniformly distributed between zero and an upper bound that is a function of the standard deviation of the proxy.¹⁴ The parameter $\bar{\sigma}_\nu$, as previously mentioned, allows us to scale a priori the amount of variance of the proxy that can be explained by measurement error. A low upper bound on σ_ν forces the estimation to generate a small measurement error and hence to take a lot of signal from the proxy. Using the priors for β and σ_ν , we can deduce a prior for ρ . In the above framework, lowering $\bar{\sigma}_\nu$ shrinks the prior on ρ toward 1. Alternatively, we could impose a prior on the reliability indicator ρ and measurement error variance σ_ν with Beta and Inverse Gamma distributions, respectively. With appropriately chosen hyperparameters, we would achieve informative priors in the same spirit as the ones described above.

Posterior Sampler. Our prior formulation does not admit a closed-form solution, so we rely on Markov chain Monte Carlo (MCMC) methods to sample the posterior. MCMC generates a sequence of random draws of parameters that, under suitable regularity conditions, converges in distribution to the posterior distribution of the model of interest.¹⁵ We partition the set of model parameters into three blocks that correspond to the reduced-form parameters (Φ, Σ) , the orthonormal matrix Ω , and the coefficients of the measurement equation (β, σ_ν) . We use a block Metropolis-Hastings algorithm, which can be described in general terms as follows. Under our prior, the posterior for all of the model parameters, *under only the VAR data* $Y_{1:T}$, can be sampled from directly because of the conjugacy of the prior distributions on (Φ, Σ) and the fact that $(\Omega, \beta, \sigma_\nu)$ do not enter the likelihood of Y_t . This object, combined with the conditional likelihood $p(M_{1:T}|Y_{1:T}, \dots)$, yields a kernel of the full posterior. Thus, we reformulate the problem as one in which this posterior is the “prior” and

¹³As emphasized by Baumeister and Hamilton (2015), a uniform prior over $\mathcal{O}(n)$ might impose unintended restrictions on other objects of the SVAR. We follow their suggestion and compare prior and posterior distributions to show how the information in the proxy updates the prior distributions for our objects of interests.

¹⁴It should be noted that $\sigma_\nu = 0$ is associated with a singular distribution for the data and proxy, which is an undesirable feature of this prior. The data are extremely informative about σ_ν , though, so this is not a practical concern.

¹⁵Del Negro and Schorfheide (2011) provide background on MCMC methods generally used in VAR models.

is updated in light of proxy. We use this prior, subject to minor adjustment, for the proposal distributions in the MCMC algorithm. Details can be found in the Appendix. This formulation is also conceptually appealing, as the difference between the prior and posterior, for all parameters, is driven solely by the proxy.

3 Data: Proxies and Corporate Credit Spreads

3.1 Measuring Monetary Policy Shocks

To construct our baseline proxy for monetary policy shocks, we apply the high-frequency event study methodology developed in [Kuttner \(2001\)](#). In this approach, the unexpected change in the target federal funds rate is measured by calculating the change in the (appropriately scaled) current-month federal funds rate futures around a tight window surrounding the release of FOMC statements. [Kuttner \(2001\)](#) uses a daily window, but subsequent studies have shown that even the use of a daily window might not be enough to purge this policy measure from expected (and hence endogenous) movements. Hence, we follow [Gürkaynak, Sack, and Swanson \(2005\)](#) and [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#) and use intraday data. In particular, we use a 30-minute window (10 minutes before and 20 minutes after).

Table 1: SUMMARY STATISTICS FOR PROXY AFTER FOMC STATEMENTS

	Basis Points		# of Observations
Median	0.0	Decrease	50
Mean	0.4	No Change	22
Std. Dev.	5.7	Positive	36
Maximum	16.3	(February 4, 1994)	
Minimum	-22.6	(December 20, 1994)	

NOTE: Table shows summary statistics for surprises in the target federal funds rate computed from current month fed funds futures contracts, along the lines of [Kuttner \(2001\)](#).

Our sample begins in January 1994, the year in which the FOMC started issuing statements immediately after each meeting, and ends in June 2007, three months before the FOMC started to cut interest rates in response to “the tightening of credit conditions [that] has the potential to intensify the housing correction and to restrain economic growth more generally.”¹⁶ This conservative cutoff ensures that we do not capture the effects of unconventional monetary policy or the presence of the zero lower bound in our baseline estimates.

¹⁶We could compute unexpected changes to the target rate using federal funds rate futures from January 1990. But prior to 1994, the FOMC did not issue a statement and changes to the target rate had to be inferred by the size and type of open market operations. [Coibion and Gorodnichenko \(2012\)](#) find an increase in the ability of financial markets and professional forecasters to predict subsequent interest rate changes after 1994, suggesting that improved transparency could have altered the transmission of policy surprises. Prior to 1994, the FOMC often changed its target for the federal funds rate just hours after the Bureau of Labor Statistics’s employment report release. But the use of intraday data avoids confounding the truly unexpected change with the reaction of the fed funds rate to the employment report. In any event, our qualitative results are robust to the inclusion in the sample of the early 1990s.

From January 1994 to June 2007, there were 108 scheduled FOMC meetings. We use the changes in the federal funds rate futures, constructed as previously discussed, after the release of the FOMC statement for each of these meetings as our baseline shock series.

Table 1 displays summary statistics for the proxy, which are plotted in Figure A-1 in Appendix B. On average, there is very little surprise change in the target federal funds rate after the release of an FOMC statement. Indeed, “no change” is the most likely outcome, with 22 of the 108 observations being zero. Overall, the changes are small. The largest decrease—an unexpected easing of policy occurring on December 20, 1994—is about 23 basis points, and the largest increase—an unexpected tightening of policy occurring on February 4, 1994—is about 16 basis points. As the right column of Table 1 shows, the shocks are negatively skewed. Almost half of the changes are negative.

We use only the changes associated with prescheduled FOMC meetings, though there are four FOMC statement releases after unscheduled FOMC meetings and phone calls.¹⁷ In general, the literature has considered shocks associated with both scheduled and unscheduled FOMC meetings.¹⁸ One exception is Nakamura and Steinsson (2013), who note that unscheduled meetings may occur in reaction to other shocks and thus be endogenous. In Appendix B, we provide statistical evidence that the inclusion of intermeeting surprises, though there are only four such observations in our sample, introduces predictability into the shock series, biasing the estimates of the effects of monetary policy. We also show that our preferred measures do not seem to contain this predictability.

Our goal is to study the effects of monetary shocks—proxied by the series of changes previously discussed—on key macroeconomic aggregates, with particular emphasis on the dynamic effects of the shocks. Unfortunately, we do not have corresponding high-frequency data for output, prices, and other objects of interest. Therefore, we convert the series of surprises to a monthly frequency. To do so, we follow Romer and Romer (2004) and assign each shock to the month in which the corresponding FOMC meeting occurred. If there are no meetings in a month, we record the shock as zero for that month.¹⁹

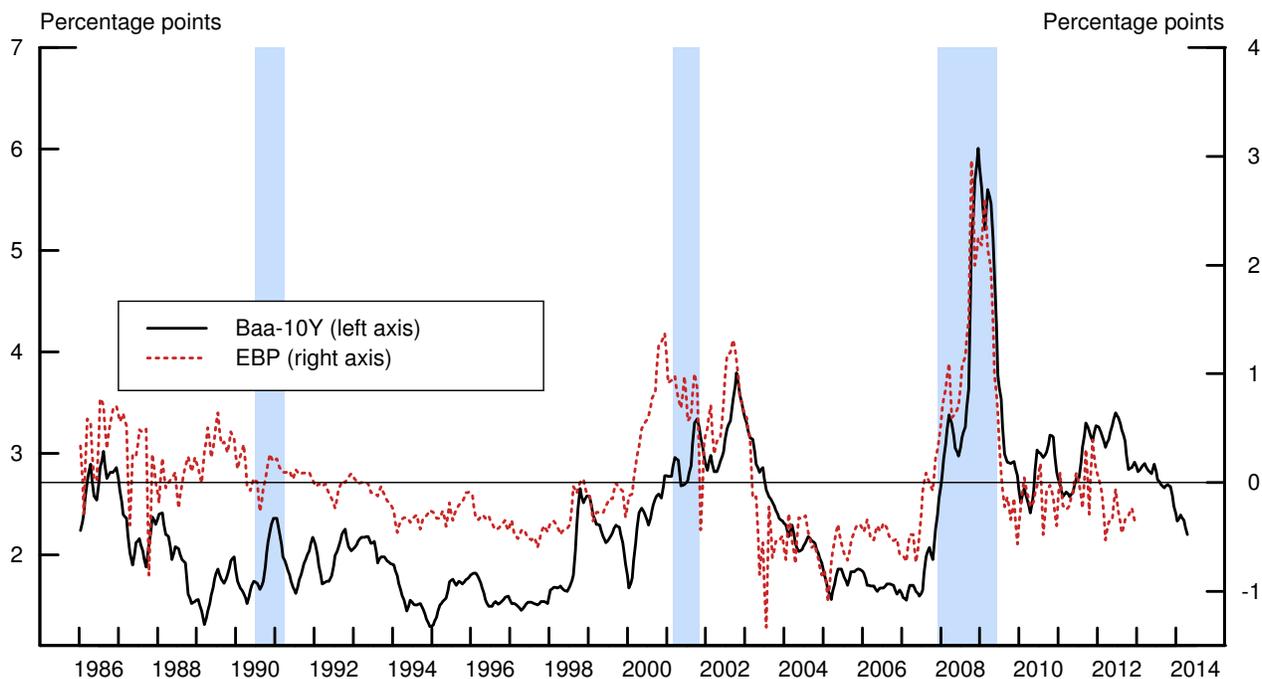
Finally, in section 5, we use the change in two-year Treasury yields in a 30-minute window around the release of the FOMC statement as an alternative proxy for the monetary shocks. Gürkaynak, Sack, and Swanson (2005) and Campbell, Evans, Fisher, and Justiniano (2012) have convincingly shown that the effects of monetary policy might be better characterized by two factors that capture changes in the current fed funds rate target and changes to the future path of policy. Gilchrist, López-Salido, and Zakrajšek (2015) argue that surprise changes in two-year Treasury yields adequately summarize the first-order effects of the

¹⁷As is customary in this kind of analysis, we do not ever include the announcement on September 17, 2001, when trading on major stock exchanges resumed after it was temporarily suspended following the 9/11 terrorist attacks.

¹⁸See, for example, Bernanke and Kuttner (2005); Gürkaynak, Sack, and Swanson (2005); Campbell, Evans, Fisher, and Justiniano (2012); Gilchrist, López-Salido, and Zakrajšek (2015); and Gertler and Karadi (2015).

¹⁹Because our baseline measure incorporates only scheduled FOMC meetings, there are never two shocks occurring in the same month.

Figure 1: CORPORATE CREDIT SPREADS



NOTE: Sample period: monthly data from January 1986 to June 2014. The red dotted line depicts the estimate of the excess bond premium, an indicator of the tightness of financial conditions (see [Gilchrist and Zakrajsek, 2012](#)). The black solid line depicts the Baa yield relative to the 10-year Treasury yield. The shaded vertical bars denote the NBER-dated recessions.

two factors.²⁰

3.2 Measuring Financial Conditions

We rely on the information contained in corporate credit spreads to measure conditions in financial markets and the transmission of monetary policy through credit markets. In particular, we use the excess bond premium (EBP), a popular indicator of tightness in credit markets constructed by [Gilchrist and Zakrajsek \(2012\)](#). The EBP estimates the extra compensation demanded by bond investors for bearing exposure to U.S. nonfinancial corporate credit risk beyond the compensation for expected losses. The U.S. corporate cash market is served by major financial institutions and fluctuations in the EBP; thus, it captures shifts in both the risk attitudes of these institutions and their willingness to bear credit risk and to intermediate

²⁰[Gilchrist, López-Salido, and Zakrajšek \(2015\)](#) also provide evidence that the proxies described above reflect unanticipated changes in monetary policy rather than policymakers private information about the state of the economy.

credit more generally in global financial markets.²¹ For robustness, we also use the Moody’s seasoned BAA corporate bond yield relative to the yield on 10-year Treasury constant maturity. We construct the monthly series by taking the average of daily observations. The advantage of the EBP over the BAA spread is that it is a more direct measure of tightness in credit markets.

Figure 1 plots the EBP and the BAA spread from 1986 to 2014. The correlation between the two measures is 0.7 for both the full sample and the 1994–2007 period used in the baseline estimation. During the Great Moderation period, the standard deviation for both indicators is around 50 basis points, compared with 60 to 75 basis points for the full sample. Hence, corporate credit markets also experienced a large amount of volatility during the Great Moderation period.

4 Monetary Policy, Real Activity, and Credit Spreads

To show how monetary policy, real activity, and credit spreads interact in a proxy SVAR, in this section we present results from two simple proxy SVAR models. We estimate a bivariate proxy SVAR model that consists of an indicator of monetary policy stance and a measure of real activity. We then add a measure of credit spreads to the bivariate model. Finally, we provide some intuition behind the key results of the section.

The bivariate VAR specification consists of the effective nominal federal funds rate and the first difference of the log of manufacturing industrial production; the trivariate specification includes the EBP.²² The resulting specifications, which include a constant, are estimated over the July 1993 to June 2007 period using six lags of the endogenous variables. For the priors, we use the Minnesota prior as in [Del Negro and Schorfheide \(2011\)](#) with hyperparameters $\lambda = [0.5, 1, 1, 1, 1]$. For β , we set $\mu_\beta = 0$ and $\sigma_\beta = 0.5$. The parameter that scales the measurement error is $\bar{\sigma}_\nu = 1$, essentially allowing all of the proxy to be measurement error. The Appendix contains details on the hyperparameters associated with the posterior sampler.

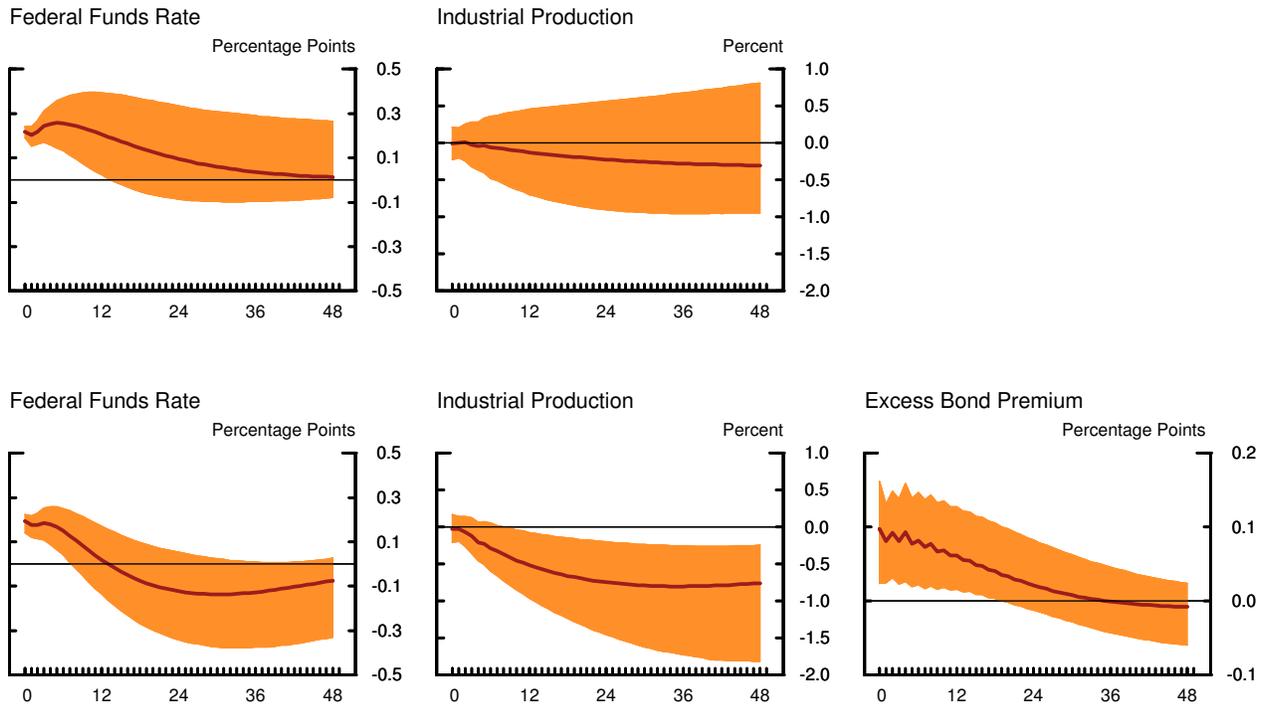
4.1 Main Results

The top panel of Figure 2 displays the impulse responses of the fed funds rate and the level of industrial production to a one standard deviation monetary shock identified using the bivariate proxy SVAR. The near-term effect of a positive monetary policy shock causes the fed funds rate to increase about 20 basis points, a number within conventional estimates. Thereafter, the fed funds rate slowly falls, returning to zero after approximately four years. There is considerable uncertainty about the effects of this shock on real activity. At

²¹This interpretation is also supported by the empirical work of [Adrian, Moench, and Shin \(2010b\)](#); [Adrian, Moench, and Shin \(2010a\)](#); and [Adrian and Shin \(2010\)](#), who show that risk premiums in asset markets are very sensitive to movements in capital and balance sheet conditions of financial intermediaries. Theoretical foundations for such “intermediary” asset-pricing theories are developed in the influential work of [He and Krishnamurthy \(2013\)](#) and [Brunnermeier and Sannikov \(2014\)](#).

²²We do not include prices in these models because, as we show in section 6, their inclusion does not change the identification of monetary policy shocks and their effects on real activity.

Figure 2: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(2-EQUATION VS 3-EQUATION MODELS)



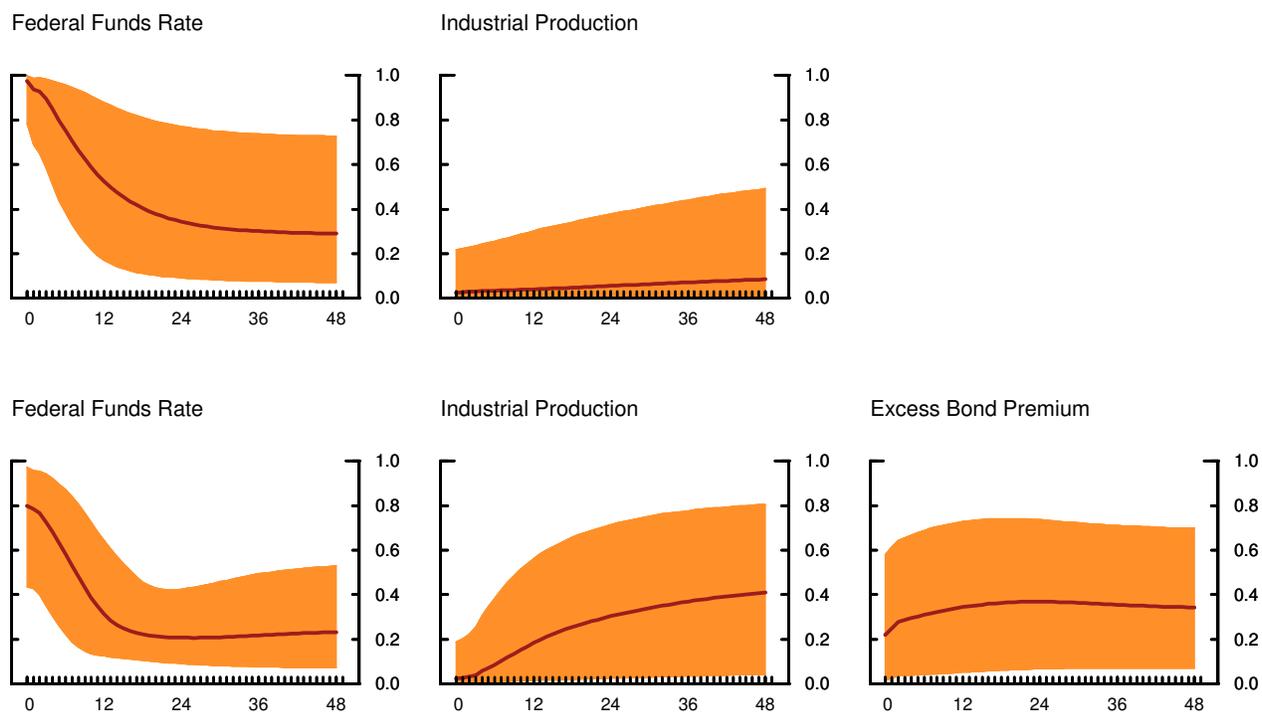
NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation monetary policy shock identified in the bivariate (top row) and in the trivariate (bottom row) proxy SVAR. The response of industrial production has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

the posterior mean estimate, the level of industrial production falls about 0.2 percent, although the posterior estimates do not rule out a positive response of real activity to the monetary tightening.

The bottom panel of Figure 2 displays the impulse responses of the federal funds rate, the level of industrial production, and the EBP to a one standard deviation monetary policy shock identified in the trivariate proxy SVAR. The impact response of the fed funds rate is 18 basis points, about the same as in the bivariate model. The impact response of industrial production is close to zero and also similar to the bivariate model. By contrast, the two models imply strikingly different dynamic effects of monetary policy shocks on these two variables. The fed funds rate falls quickly after the shock and turns negative—monetary policy becomes more accommodative, relative to its initial level—after about two and a half years. The effect of the shock on real activity is large. About two and a half years after the shock, the level of industrial production has fallen about 0.75 percent.

The difference in responses between models is clearly due to the inclusion of corporate credit spreads. In response to the monetary tightening, there is a sustained increase in the credit spread, which begins at

Figure 3: CONTRIBUTION TO THE FORECAST ERROR VARIANCE OF MONETARY POLICY SHOCKS
(TWO EQUATION VS THREE EQUATION MODELS)

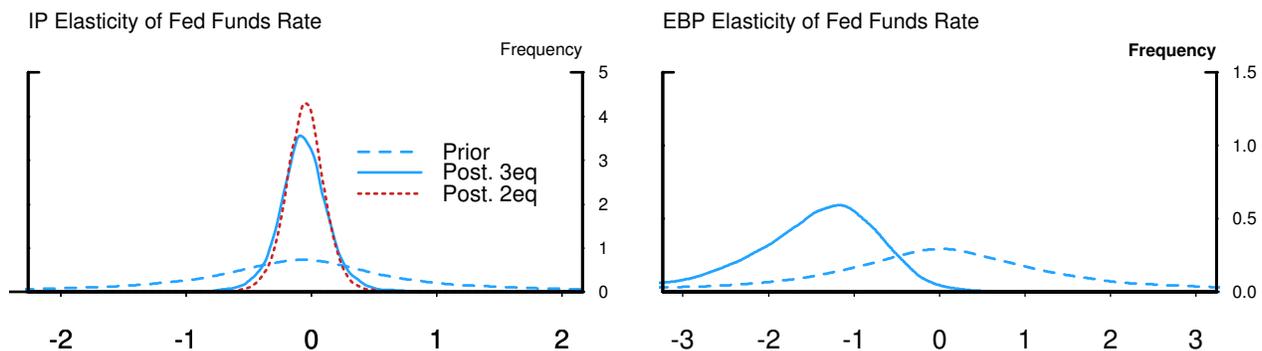


NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a one standard deviation monetary policy shock identified in the bivariate (top panel) and in the trivariate (bottom panel) proxy SVAR. The forecast error variance decomposition of industrial production is based on the level of the variable. Shaded bands denote the 90 percent pointwise credible sets.

about 10 basis points over its baseline level and remains above zero for over two years. As discussed in the next subsection, the tightening in financial conditions and the reduction in real activity explain the fall in the fed funds rate, as monetary policy endogenously reacts to the state of the business and financial cycles. Hence, corporate credit spreads are both an important conduit of changes in monetary policy to the real economy and important to quantifying the endogenous response of monetary policy to a deterioration in real and financial conditions.

The previously discussed results are suggestive of large differences between models about the importance of monetary shocks for business cycle fluctuations. Using the VAR structure, we can decompose the forecast error of the VAR along different horizons, attributing portions of the error variance to monetary shocks. The top panel of Figure 3 displays these quantities for the monetary shock identified in the bivariate model, and the bottom panel displays these quantities for the monetary shock identified in the trivariate model. Concentrating on the horizons associated with business cycle frequencies—that is, 12-36 months—we see that in the bivariate model, the monetary policy shock explains a negligible fraction of short-run movements

Figure 4: SYSTEMATIC COMPONENT OF MONETARY POLICY



NOTE: The two plots correspond to density estimates of the SVAR elasticities $\eta_{\Delta IP}$ and η_{EBPP} . The blue dashed lines show estimates of $p(\eta|Y_{1:T})$ for the trivariate proxy SVAR, the blue solid lines show estimates of $p(\eta|Y_{1:T}, M_{1:T})$ for the trivariate proxy SVAR, and the red dash-dotted line shows estimates of $p(\eta_{\Delta IP}|Y_{1:T}, M_{1:T})$.

in industrial production, in line with the conventional wisdom that monetary policy does not contribute to business cycle fluctuations. The decomposition is dramatically different for the trivariate model. Monetary policy accounts for up to 40 percent of the fluctuations of industrial production and of the EBP.

As we show in section 6, in larger models the contribution of monetary policy to movements in industrial production drops from 40 percent to about 20 percent. Nonetheless, the pattern documented in this section holds: The dynamic effects of monetary shocks on the real economy are substantially larger and more precisely estimated with the inclusion of a measure of corporate credit spreads in the VAR.

4.2 Discussion

To further understand the connections between monetary policy, real activity, and credit conditions, let us consider the following parameterization of the relationship between the reduced-form residuals and structural shocks:

$$u_{1,t} = \eta u_{2,t} + S_1 e_{1,t}, \quad (17)$$

$$u_{2,t} = \xi u_{1,t} + S_2 e_{2,t}, \quad (18)$$

where $u_{1,t}$ and $e_{1,t}$ are the reduced-form and structural federal funds rate innovations, respectively, and $u_{2,t}$ and $e_{2,t}$ contain the reduced-form residuals and structural shocks associated with the remaining variables in the VAR, respectively. The intuition of how the proxy SVAR identifies the monetary shock $e_{1,t}$ is that, under assumptions (9) and (10), m_t is a valid instrument for $u_{1,t}$ to estimate ξ in Equation (18). Given the

estimate for ξ , $u_{2,t} - \xi u_{1,t}$ is a valid instrument to estimate η in Equation (17).

As shown in Equation (17), given some reduced-form residuals, the identification of $e_{1,t}$ hinges on the identification of η , the contemporaneous elasticities of the federal funds rate to changes in real activity ($\eta_{\Delta IP}$) and credit spreads (η_{EBP}). This interpretation of identification in SVARs is consistent with [Leeper, Sims, and Zha \(1996\)](#); [Leeper and Zha \(2003\)](#); and [Sims and Zha \(2006\)](#), who emphasize that the identification of policy shocks is equivalent to the identification of a policy equation—that is, of the endogenous component of policy.

Figure 4 plots the densities for these elasticities considering only the VAR observables $p(\eta|Y_{1:T})$ —the prior distributions discussed in section 2—and the posterior densities $p(\eta|Y_{1:T}, M_{1:T})$ having observed the proxy for both the bivariate and trivariate models.²³ The prior distributions, the blue dashed lines, are centered at zero and have a very wide coverage so that the model does not rule out any plausible value for these elasticities before observing the proxy. The posterior distributions in both models are clearly updated in light of the information contained in the proxy. The posterior distribution of $\eta_{\Delta IP}$ in the bivariate model (the red dotted line) and in the trivariate model (the blue solid line) are very similar, centered around zero and with very little variation. Hence, the information in the proxy m_t suggests that the fed funds rate does not respond contemporaneously to changes in industrial production.²⁴ This result also corroborates the fact that the BP-SVAR consistently estimates the contemporaneous coefficients that relate the proxy to the variables *included* in the model, even in models with different dynamic structures. The posterior distribution for η_{EBP} is clearly different from zero, with a median of negative 0.48 and a 90 percent credible set that ranges from negative 1.19 to negative 0.05. A one standard deviation increase in u_{EBP} —approximately 20 basis points—all else being equal, elicits an immediate monetary policy accommodation of 10 basis points.

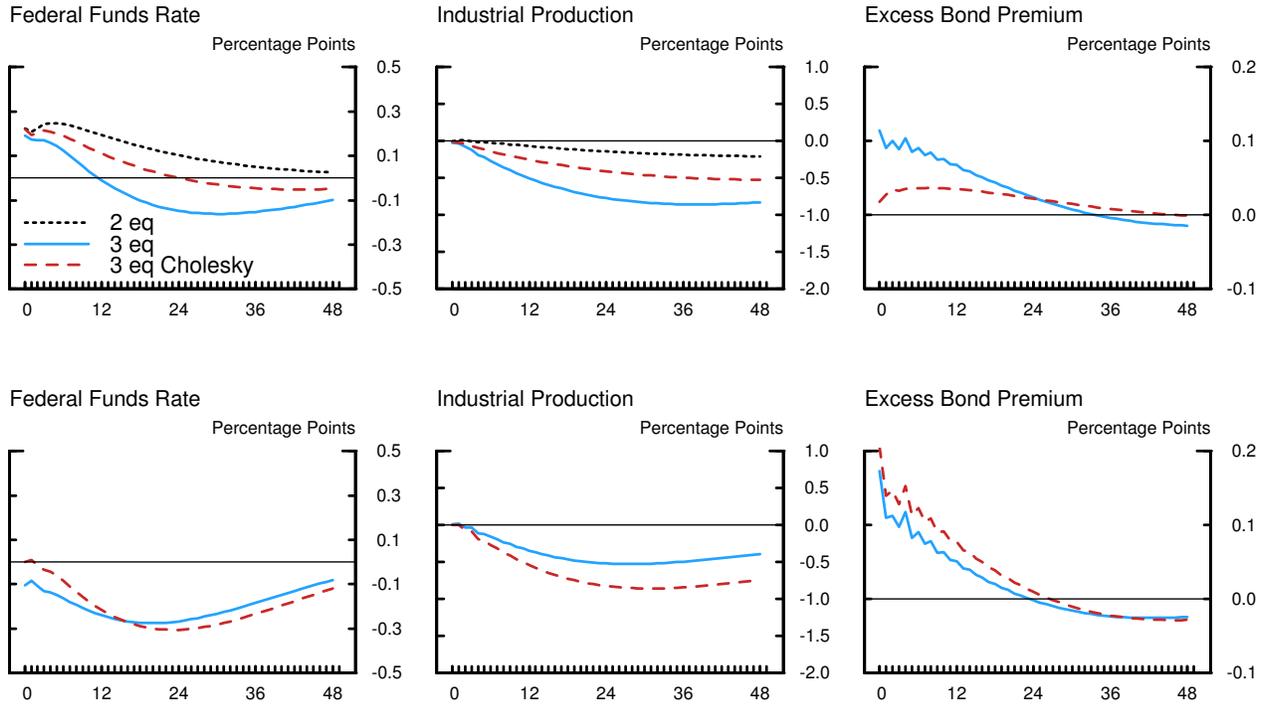
This significant coefficient on the EBP suggests that, through the lense of the trivariate model, the bivariate model identifies a monetary shock that is contaminated by the contemporaneous endogenous response of monetary policy to credit spreads. Of course, a second reason that the identified monetary policy shock changes across models is that the addition of the EBP changes the dynamics of the model. For instance, the fed funds rate (or industrial production) could react to lagged values of the EBP. In this case, the identified monetary shocks would be different in a model that includes EBP, even if $\eta_{EBP} = 0$.

To understand the relative importance of these two potential sources of model misspecification, we explore an alternative identification strategy based on a Cholesky factorization of Σ , in which the fed funds rate does not contemporaneously react to industrial production and the EBP. The top panel of Figure 5 compares im-

²³The prior distributions are identical in both models.

²⁴In Section 6 we show that this finding holds when using alternative measures of real activity, for example, changes in employment and consumption.

Figure 5: MACROECONOMIC IMPLICATIONS OF MONETARY POLICY AND FINANCIAL SHOCKS
(MODEL COMPARISON)



NOTE: Each panel depicts the impulse responses of the specified variable to a one standard deviation monetary policy shock (top row) and financial shock (bottom row) under three identification schemes: bivariate proxy SVAR (black dotted line), trivariate proxy SVAR (blue solid line), and trivariate Cholesky factorization (red dashed line). Impulse responses are evaluated at the OLS estimates of the reduced-form coefficients. The response of industrial production has been accumulated. See text for additional details.

pulse responses to a monetary policy shock computed at the OLS estimates of the reduced-form coefficients.²⁵ The impulse responses from the bivariate proxy SVAR (the black dotted lines) and the trivariate proxy SVAR (the blue solid lines) are similar to the median responses plotted in Figure 2. The impulse responses identified with the Cholesky decomposition fall in between the responses from the two proxy SVARs. The response of industrial production to a monetary shock peaks at about negative 0.5, twice as large than in the bivariate proxy SVAR but 40 percent smaller than the response estimated in the trivariate proxy SVAR. Similarly, the impact response of the EBP is 0.02, about five times smaller compared with the trivariate proxy SVAR.

The bottom panel of Figure 5 displays the impulse responses of the fed funds rate, the level of industrial production, and the EBP to a one standard deviation financial shock identified in the trivariate proxy SVAR

²⁵The impulse responses to the monetary policy shock would look nearly identical had we plotted median responses from the full Bayesian estimation of the models. We choose to plot results for a simple OLS estimation where the proxy SVAR is identified using the algorithm in Mertens and Ravn (2013) because—in light of the recent work by Arias, Rubio-Ramirez, and Waggoner (2014)—the posterior sampler would need to be modified to properly impose the zero restrictions used to identify the financial shock. Moreover, we also wanted to highlight that our results hold for the standard implementation of the proxy SVAR and are not specific to the Bayesian framework.

and using the Cholesky identification. In the latter approach, the EBP is ordered last in the system, and hence a financial shock cannot contemporaneously affect the fed funds rate and industrial production. Because we do not have a proxy to identify exogenous movements in the EBP, in the proxy SVAR we identify the financial shock by imposing a similar recursive ordering. In particular, we assume that the EBP is ordered last within the nonpolicy block $u_{2,t}$, which amounts to imposing lower triangular structure on S_2 from Equation (18). Note that the proxy SVAR allows the financial shock to have a contemporaneous effect on the fed funds rate, and this effect is pinned down by the identification of the monetary shock, and in particular by the elasticity of the fed funds rate to the EBP. These results suggest that, through the lense of the trivariate model, the bivariate model identifies a monetary shock that is contaminated by the contemporaneous endogenous response of monetary policy to credit spreads. A complementary explanation is that the addition of the EBP changes the dynamics of the model. For instance, the fed funds rate (but also industrial production) could react to lagged values of the EBP, and hence the identified monetary shocks would be different in a trivariate model even if η_{EBP} , which is negative in our model, were zero. Consequently, the financial shock cannot *directly* affect industrial production on impact but it can affect industrial production indirectly through the fed funds rate.²⁶

Following a financial shock identified in the proxy SVAR, the EBP goes up approximately 15 basis points on impact and remains above zero for about two years. The fed funds rate drops about 10 basis points on impact and remains accommodative thereafter. The immediate accommodation in the monetary stance partially offsets the effect of the financial shock on real activity, and industrial production falls about 0.5 percent, a smaller drop compared with the one induced by monetary policy shocks.

Following a financial shock identified with the Cholesky factorization, the EBP goes up slightly more than in the proxy SVAR. By assumption, the fed funds rate cannot respond contemporaneously to the financial shocks. Industrial production falls more than in the proxy SVAR. The lack of immediate reaction from the monetary authority induces a more persistent decline in real activity and a more sustained rise in the EBP, which in turn leads the stance of monetary policy to be more accommodative for longer. Hence, the identification of the monetary shock in the proxy SVAR has important implications for the propagation of other shocks in the system.

Finally, Figure 5 makes clear that, through the lense of the proxy SVAR, the monetary shock identified with a Cholesky factorization is contaminated by the endogenous response of monetary policy to the EBP. Because (i) $\eta_{EBP} < 0$ and (ii) increases in the EBP are associated with future low economic activity, it follows that the failure to control for the endogenous response of monetary policy to credit market conditions

²⁶The idea is to compare the identification of a financial shock using a “full” Cholesky to a block Cholesky, where the only difference is in the identification of the monetary shock via the proxy.

Table 2: RELIABILITY INDICATORS

A. Baseline (fed funds rate)		
	$\bar{\sigma}_\nu = 1$	$\bar{\sigma}_\nu = 0.5$
Bivariate	0.11 [0.04, 0.20]	0.33 [0.24, 0.43]
Trivariate	0.11 [0.04, 0.20]	0.33 [0.24, 0.43]
B. Alternative (two-year Treasury yield)		
	$\bar{\sigma}_\nu = 1$	$\bar{\sigma}_\nu = 0.25$
Four Equation	0.01 [0.00, 0.05]	0.18 [0.09, 0.29]

NOTE: Panel A reports the estimates of the reliability indicator associated with the bivariate and trivariate proxy SVARs for a loose ($\bar{\sigma}_\nu = 1$) and tight ($\bar{\sigma}_\nu = 0.5$) prior on the standard deviation of the measurement error. Similarly, panel B reports the estimates of the reliability indicator associated with the four equation proxy SVAR model for a loose ($\bar{\sigma}_\nu = 1$) and tight ($\bar{\sigma}_\nu = 0.25$) prior on the standard deviation of the measurement error. The proxy is the surprise changes in two-year Treasury yields calculated by [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#). See the text for details.

induces an attenuation bias in the responses of the EBP and industrial production to a monetary shock.²⁷

5 Reliability and Prior Specification

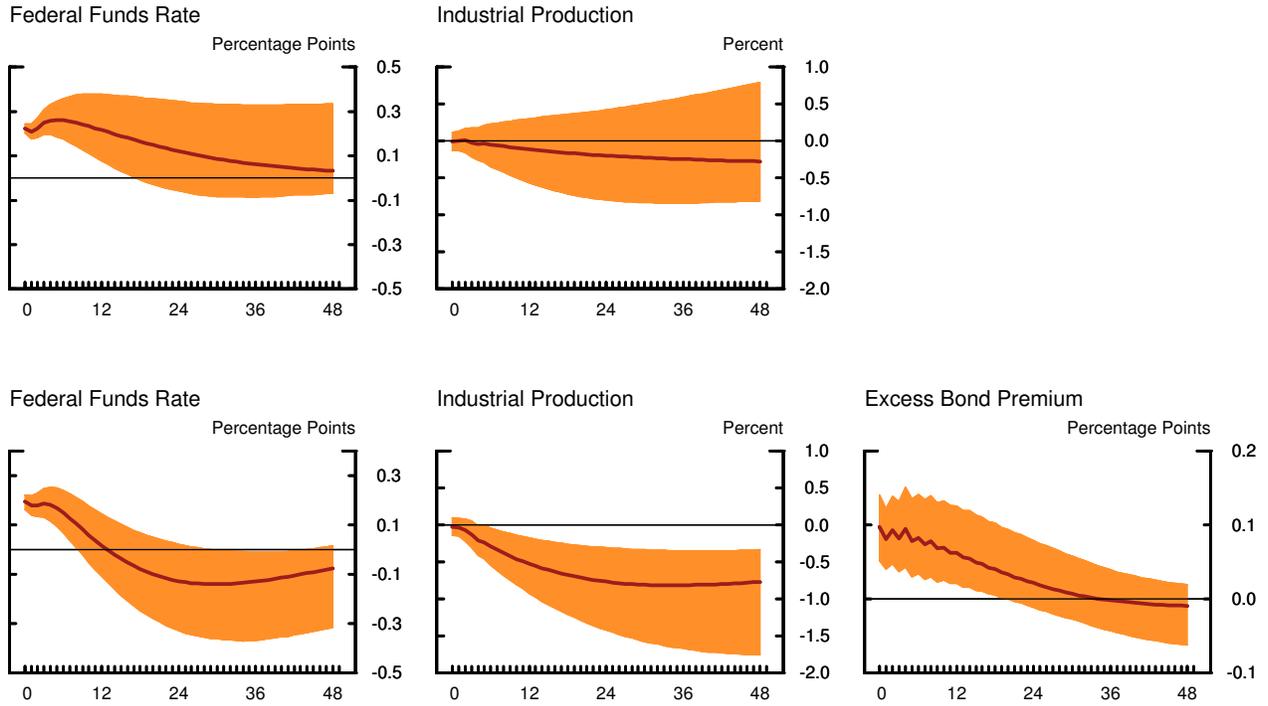
In the previous section, we documented how the inclusion of a variable in the proxy SVAR—namely, a measure of credit spreads—has dramatic effects on inference. This result suggests that model misspecification in the form of omitted variables, a serious concern when estimating standard SVARs, is also a serious concern when working with proxy SVARs. But are there statistics that we can use to detect this type of model misspecification?

The reliability indicator presented in Equation (9) is a metric of how relevant a proxy is for the identification of a shock of interest. This indicator might be a helpful statistic because VARs that miss key variables might be associated with low reliability indicators. The first column of Table 2 presents the posterior estimates of the reliability indicator ρ described for the bivariate and trivariate proxy SVARs. The median is 0.11 for both models, and the 5th and 95th percentiles are 0.04 and 0.20, respectively. Despite having very different implications, the two models have equal reliability indicators.²⁸

²⁷It should be noted that this contamination is not related to the fact that the proxy contains measurement error. Evidence from Monte Carlo experiments (not shown) confirms that even when the proxy contains very little measurement error, the estimates of the elasticities are still biased if variables in the data-generating process (for example, credit spreads) are omitted from the proxy SVAR. The Cholesky factorization will similarly provide biased estimates.

²⁸The reliability indicator for the trivariate model is larger than in the bivariate model at the third decimal digit.

Figure 6: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(TIGHT PRIOR ON $\bar{\sigma}_\nu$)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified in the bivariate (top row) and in the trivariate (bottom row) proxy SVAR estimated with a tight prior on the measurement error ($\bar{\sigma}_\nu = 0.5$). The response of industrial production has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

One interpretation might be that both models are misspecified, and hence the reliability indicator is equal and *small* in both models. One exercise that our Bayesian framework allows us to perform is to tighten the prior on the measurement error and force the proxy SVAR to take more signal from the proxy than in the baseline estimation. For instance, we impose that $\bar{\sigma}_\nu = 0.5$ —that is, the measurement error can explain, at most, half of the variation in the proxy. As we report in the second column of Table 2, a tight prior on $\bar{\sigma}_\nu$ increases the reliability of both models to 0.33, which implies a correlation between $e_{1,t}$ and m_t of nearly 0.6.²⁹

Figure 6 plots the associated impulse responses to a one standard deviation monetary policy shock for the bivariate and trivariate proxy SVARs. The impulse responses are nearly indistinguishable from those reported

²⁹When we set a tight bound on the standard deviation of the measurement error, most of the probability mass in the posterior distribution for σ_ν is concentrated at $\bar{\sigma}_\nu$. By choosing an extreme prior for σ_ν , we convey in stark terms the lack of relationship between the reliability indicator and the dynamics of the BP-SVAR, which a more flexible prior setting might obscure. Moreover, one could argue that we could achieve the same analysis by simply fixing this measurement error and estimating the model via maximum likelihood estimation. Note, however, that because of the nondogmatic prior on β , the implied prior on the reliability ρ is still nondogmatic, as clearly indicated by the distributions reported in Table 2.

in Figure 2. This result suggests that both the bivariate and trivariate proxy SVARs are well identified *for the set of variables included in the model* and, consequently, changing the prior distributions of some parameters does not change the posterior.

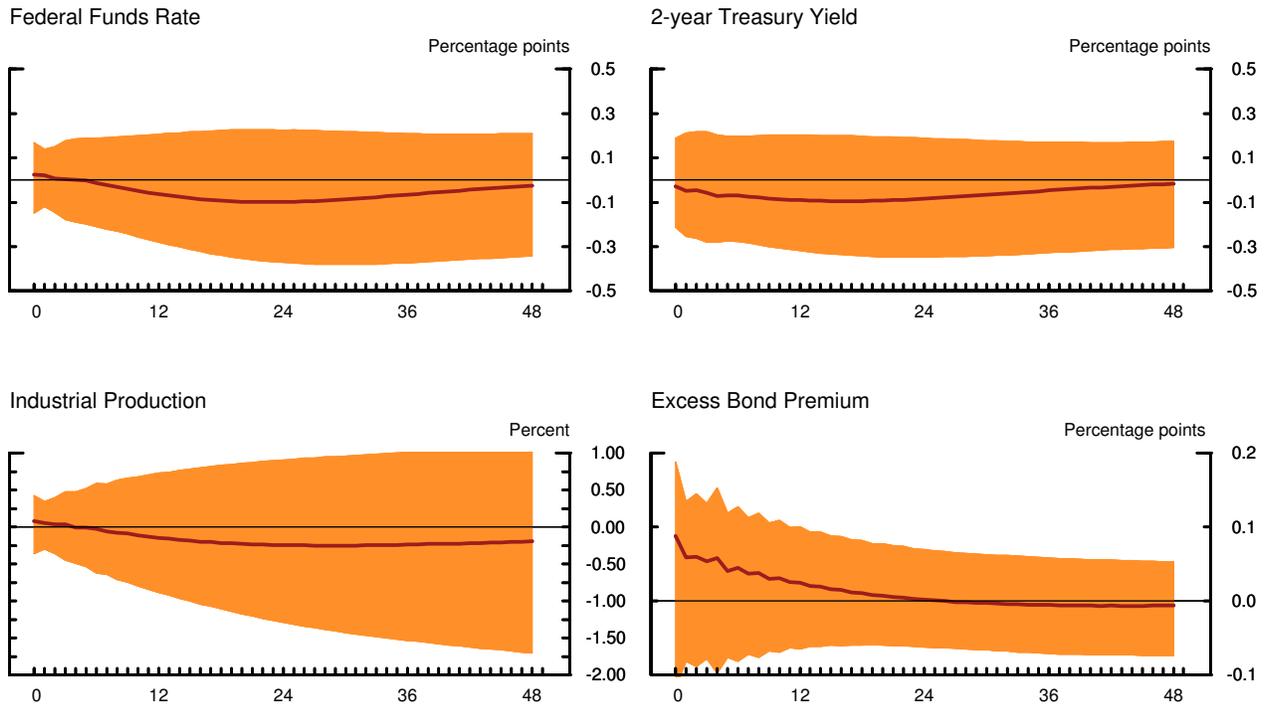
We now turn to an application that shows the potential of the Bayesian framework when applied to models that are not well-identified. Specifically, motivated by the work of [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#) described in Section 3, we use an alternative proxy for the unobserved monetary policy shocks, the surprise changes in the two-year Treasury yield. Accordingly, we expand the model and add the two-year Treasury yield to the three variables we have in the baseline specification.

Figure 7 reports the impulse responses to a one standard deviation monetary policy shock for the baseline estimation of the model where we set $\bar{\sigma}_\nu = 1$. None of the responses is statistically different from zero, and the error bands are extremely wide. Interestingly, the median impact response of the EBP is 0.1, in line with the response found in our baseline model. But the posterior distribution has a very fat right tail with the 5th percentile equal to negative 0.1. Overall, the evidence from this proxy SVAR suggests that the so-called path factor—here encompassed in the change in the two-year Treasury yield—is a much weaker driver of asset prices than the conventional monetary policy (level) shocks studied in Section 4.1. This finding is contrary to much of the literature, which estimates the response of asset prices to monetary policy shocks (for example, [Gürkaynak, Sack, and Swanson, 2005](#).) The reason for this discrepancy is that the proxy SVAR attributes nearly all of the movements in the proxy to measurement error. Indeed, the width and irregularity of the posterior densities, especially of the response of the EBP, suggest that the model might not be well identified. The reliability indicator, reported in the last row of Table 2, is only 0.01.

Figure 8 reports the impulse responses obtained by re-estimating the model with a tight prior on the standard deviation of the measurement error, which we assume can explain at most one-fourth of the standard deviation of the proxy. Forcing the proxy SVAR to take a lot of signal from the proxy has notable effects on results. The response of the two-year Treasury yield is negative across the response horizon. This response might seem odd, given that we are studying a monetary policy tightening but is fully consistent with the response of the fed funds rate. Because a monetary policy shock has large and persistent detrimental effects on both financial conditions and real activity, an initial tightening in policy is followed by a loosening that peaks exactly two years after the shock. The cumulative response of the fed funds rate over a two-year rolling window is nearly identical to the response of the two-year yield. The response of EBP to the identified monetary policy shock is more precisely estimated with a positive and persistent effect—much closer to effects estimated using an event-study methodology.

Figure 9 plots the prior and posterior densities for the elasticities of the fed funds rate to industrial production and the EBP elasticities. In the baseline estimation where we set $\bar{\sigma}_\nu = 1$, the distribution of

Figure 7: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(LOOSE PRIOR ON $\bar{\sigma}_\nu$)

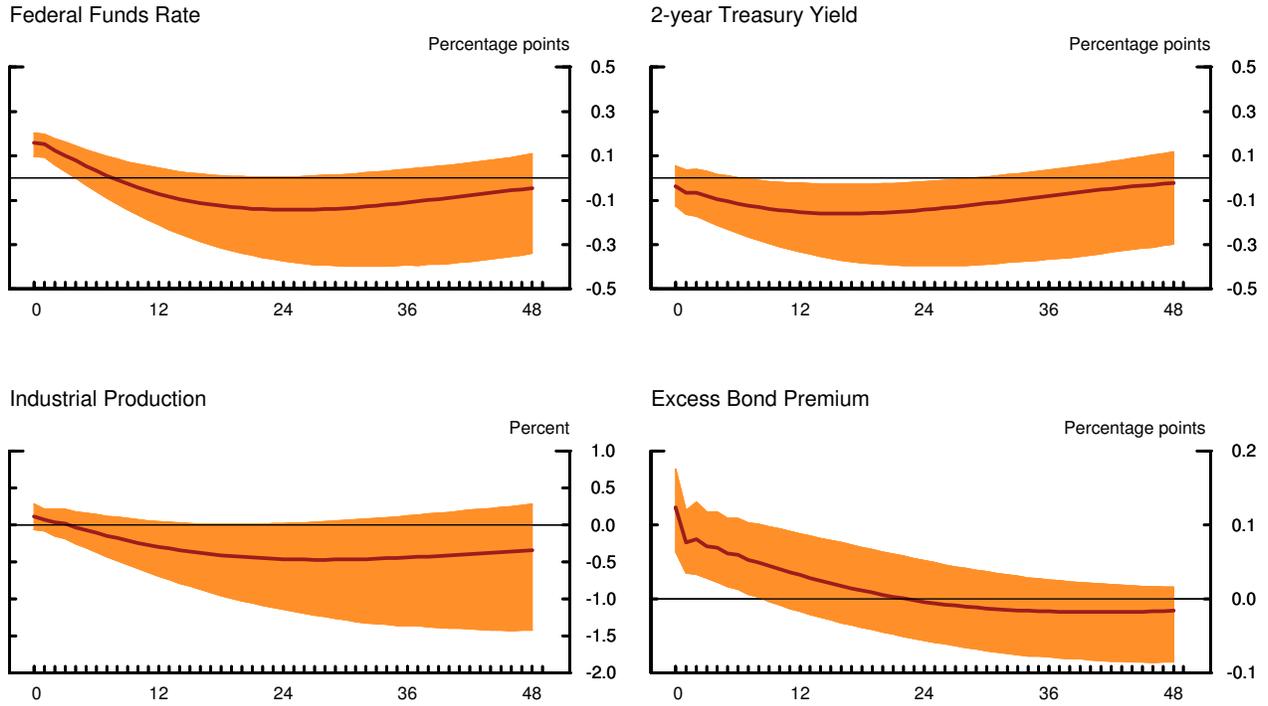


NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified with a four equation proxy SVAR with a loose prior on the measurement error ($\bar{\sigma}_\nu = 1$). Shaded bands denote the 90 percent pointwise credible sets. The proxy is the surprise changes in two-year Treasury yields calculated by [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#). The response of industrial production has been accumulated. See text for details.

both $\eta_{\Delta IP}$ and η_{EBP} is clearly not updated and the two distributions clearly overlap. By contrast, posterior distributions are clearly updated when we force the proxy SVAR to take a lot of signal from the proxy, and the elasticities are similar to those shown in Figure 4.

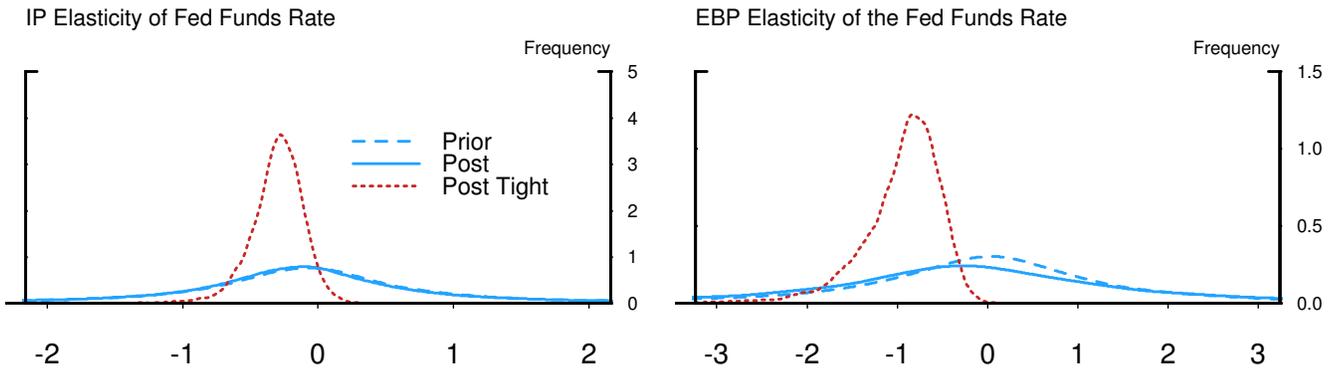
All told, three messages emerge from this section. First, the reliability indicator does not seem to capture model misspecification and cannot be used for cross-model comparison. Second, the Bayesian framework allows us to explore inference for varying degrees of reliability. When the proxy SVAR is only weakly identified, forcing a small measurement error can substantially reduce noise and sharpen inference. Third, our framework allows us to recover sharp predictions on the effects of monetary policy shocks when the latter are proxied by movements in yields at longer maturities.

Figure 8: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(TIGHT PRIOR ON $\bar{\sigma}_\nu$)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified with a four equation proxy SVAR with a tight prior on the measurement error ($\bar{\sigma}_\nu = 0.25$). Shaded bands denote the 90 percent pointwise credible sets. The proxy is the surprise changes in two-year Treasury yields calculated by [Gilchrist, López-Salido, and Zakrajšek \(2015\)](#). The response of industrial production has been accumulated. See text for details.

Figure 9: SYSTEMATIC COMPONENT OF MONETARY POLICY



NOTE: The two plots correspond to density estimates of the SVAR elasticities $\eta_{\Delta IP}$ and η_{EBP} . The blue dashed lines show estimates of $p(\eta|Y_{1:T})$, the blue solid lines show estimates of $p(\eta|Y_{1:T}, M_{1:T})$ when $\bar{\sigma}_\nu = 1$, and the red dash-dotted lines show estimates of $p(\eta|Y_{1:T}, M_{1:T})$ when $\bar{\sigma}_\nu = 0.25$.

6 Application to Larger Models

In section 4, we explored the macroeconomic implications of monetary shocks identified in small proxy SVARs consisting of two and three variables. We also argued, providing additional evidence in section 5, that the omission of credit spreads from the model has large effects on inference. In this section, we characterize the effects of monetary policy using larger models taken from the literature. We want to study whether the inclusion of more variables leads to further changes in results, and whether the omission of credit spreads from larger models leads to the same change in inference as in the small model.

6.1 Gertler and Karadi (2015)

The first model we estimate is the proxy VAR employed in Gertler and Karadi (2015). The model consists of seven variables. To the three variables used in our baseline model we add the following: the first difference of the personal consumption expenditure (PCE) price level excluding food and energy, the 10-year Treasury yield, the prime mortgage spread over 10-year Treasury yields, and the commercial paper spread.³⁰ Our proxy is the surprise component in the current-month fed funds rate future, but results are robust to the use of the three-month-ahead monthly fed funds futures as in Gertler and Karadi (2015).

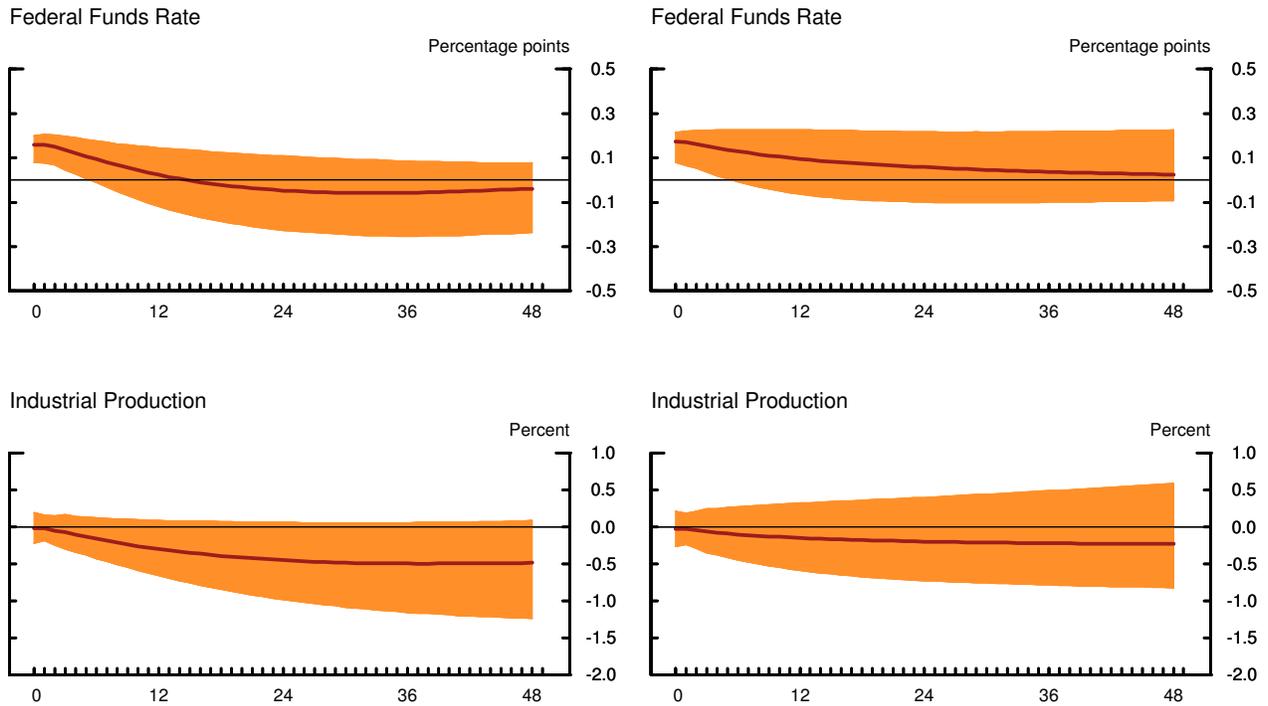
Figure 10 displays the impulse responses of the federal funds rate and the level of industrial production to a one standard deviation monetary shock identified in the full model (left column) and in an identically specified model that omits the EBP (right column). Figures A.2 and A.3 in Appendix C display the impulse responses of all remaining variables. Two results emerge from this exercise. First, in the full model, the decline in industrial production is smaller than in the trivariate proxy SVAR and bottoms at negative 0.5 after about three years. The decline in real activity and increase in the EBP lead monetary policy to relax its stance after about two years. But the loosening of the stance is smaller than in the trivariate proxy SVAR and is not statistically significant. Second, the omission of the EBP from the baseline model leads to the same bias toward zero in the estimated response of industrial production that we documented in section 4.

Figure 11 displays the fraction of forecast error variance in industrial production attributed to the monetary shock in the full model and in the model without the EBP. Figures A.4 and A.5 in Appendix C display the forecast error variance decomposition of all remaining variables. Although the monetary shock identified in the full model explains up to 20 percent of movements in industrial production, the same shock explains less than 5 percent in the model without the EBP. Hence, the other financial variables in the system do not mitigate the omitted variable bias induced by the removal of the EBP.

To understand why the inclusion of the EBP is crucial to the identification of monetary policy shocks

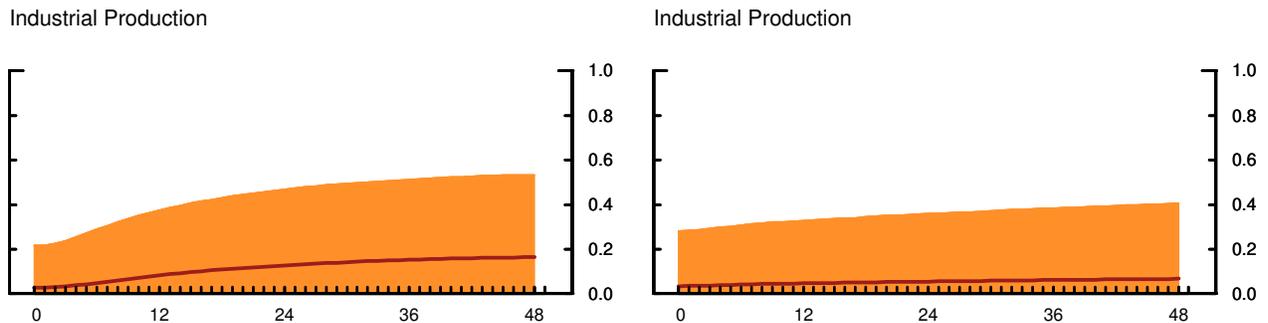
³⁰Gertler and Karadi (2015) estimate many specifications that rotate government yields. We take one particular specification that includes the 10-year Treasury yield, but results are robust to the use of yields on Treasury securities at different maturities.

Figure 10: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
 (SELECTED VARIABLES FROM THE GERTLER AND KARADI (2015) VAR MODEL)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified in the Gertler and Karadi (2015) VAR model (left column) and in the same model without the EBP (right column). The response of industrial production has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

Figure 11: CONTRIBUTION TO THE FORECAST ERROR VARIANCE OF MONETARY POLICY SHOCKS
 (SELECTED VARIABLES FROM THE GERTLER AND KARADI (2015) VAR MODEL)



NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of the level of industrial production attributable to a one standard deviation monetary policy shock identified in the Gertler and Karadi (2015) VAR model (left column) and in the same model without the EBP (right column). Shaded bands denote the 90 percent pointwise credible sets.

Table 3: ELASTICITY OF FEDERAL FUNDS RATE TO MACRO AND FINANCIAL VARIABLES
(GERTLER AND KARADI (2015) VAR MODEL)

	10Y	ΔP	ΔIP	MTGS	CPS	EBP
Full Model	-0.08	-0.04	0.00	-0.04	0.01	-0.10*
No EBP	-0.11	-0.01	0.01	-0.10	0.02	–

NOTE: The table reports the median estimates of the elasticity of the federal funds rate to macroeconomic and financial variables estimated in five proxy SVARs. *: 68 percent credible set does not include zero; **: 90 percent credible set does not include zero. The elasticities are standardized by the OLS estimate of the standard deviation of the relevant reduced-form residual; 10Y: 10-year Treasury yield; ΔP : personal consumption expenditure price deflator (first difference); ΔIP : manufacturing industrial production (first difference); MTGS: mortgage spread; CPS: commercial paper spread; EBP: excess bond premium.

in a model that also contains several financial variables, Table 3 reports the estimated contemporaneous elasticities of the fed funds rate to changes in all other variables in the system for the two variants of the Gertler and Karadi (2015) proxy SVAR model. To enhance comparability, the elasticities are standardized by the standard deviation of the VAR reduced-form residual of the relevant variable. The posterior distribution of all elasticities has substantial probability mass on both positive and negative values for all variables but the EBP, whose distribution has substantial mass on negative values. Monetary policy does not react contemporaneously to changes in spreads on mortgage and commercial paper, which explains why their inclusion in the VAR does not change the identification of monetary shocks.³¹ Moreover, and in contrast with standard monetary policy rules routinely used in macroeconomic models, the information in the proxy does not identify any contemporaneous and systematic response of monetary policy to changes in prices. This result, together with the lack of response of prices to a monetary policy shock, motivates the exclusion of prices from the VAR specifications studied in section 4.

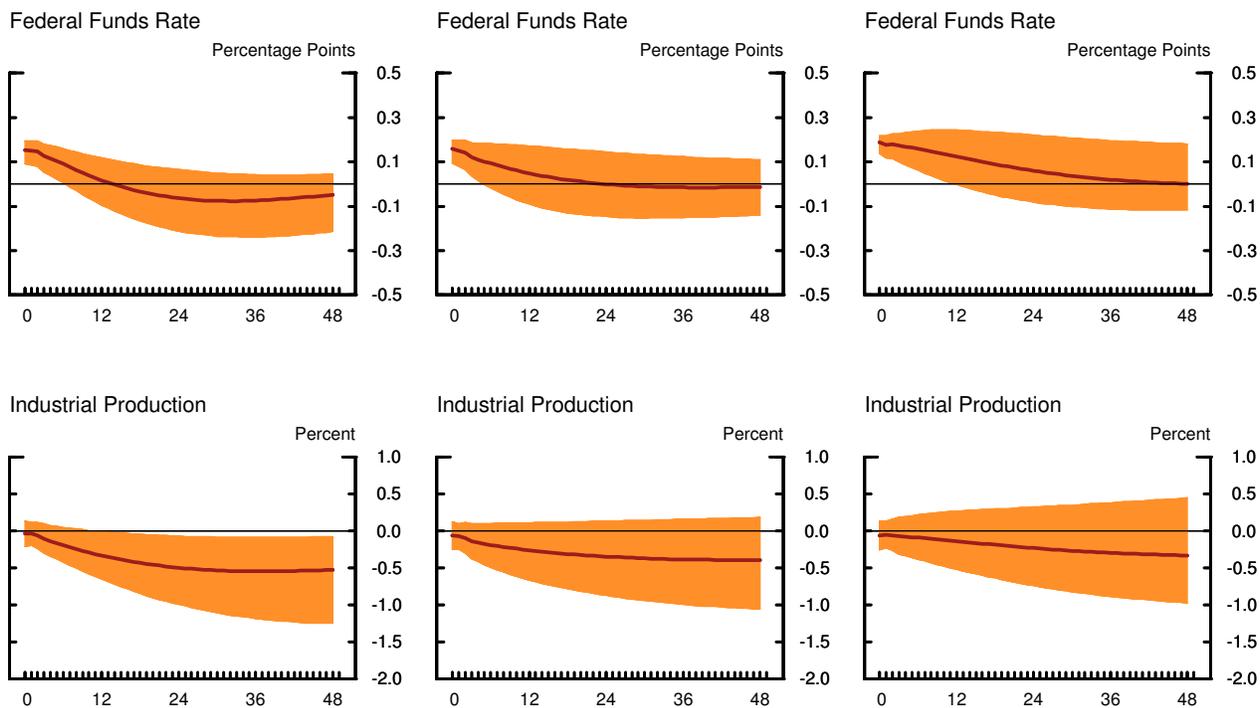
6.2 Gilchrist and Zakrajsek (2012)

The second model we estimate is a monthly version of the SVAR employed in Gilchrist and Zakrajsek (2012) and used in Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) to study the effects of financial and uncertainty shocks. To the three variables we use in the baseline model we add the following: the first difference of the log of private (nonfarm) payroll employment, the first difference of the log of (real) PCE, (6) the first difference of the log of the PCE price deflator excluding food and energy, the 10-year Treasury yield, and the first difference of the value-weighted total stock market (log) return.

Figure 12 displays the impulse responses of the federal funds rate and the level of industrial production to a one standard deviation monetary shock identified in the full model (left column), in an identically specified

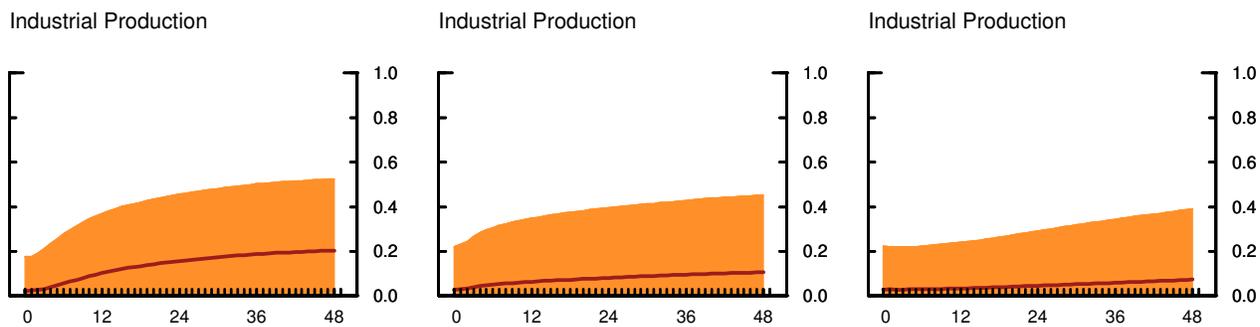
³¹Results are consistent with Bjørnland and Jacobsen (2013), who also finds that the response of the fed funds rate to a house price shock is smaller than the response to a stock price shock.

Figure 12: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without the EBP and without the excess stock market return. The response of industrial production has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

Figure 13: CONTRIBUTION TO THE FORECAST ERROR VARIANCE OF MONETARY POLICY SHOCKS
(SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of the level of industrial production attributable to a one standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without the EBP and without the excess stock market return. Shaded bands denote the 90 percent pointwise credible sets.

Table 4: ELASTICITY OF THE FEDERAL FUNDS RATE TO MACRO AND FINANCIAL VARIABLES
(GILCHRIST-ZAKRAJŠEK VAR MODEL)

	10Y	ΔP	ΔIP	ΔPCE	ΔEmp	EBP	SMR
Full Model	-0.01	-0.04	0.05	-0.02	-0.06	-0.06*	0.09*
No EBP	-0.02	-0.01	0.07	-0.04	-0.05	–	0.12**
No EBP & SMR	-0.01	0.00	0.04	-0.02	-0.04	–	–

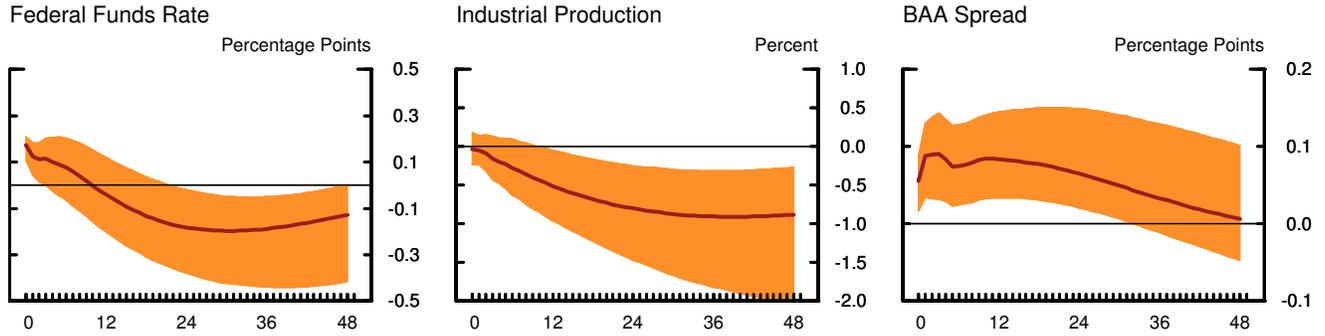
NOTE: The table reports the median estimates of the elasticity of the federal funds rate to macroeconomic and financial variables estimated in three proxy SVARs. *: 68 percent credible set does not include zero; **: 90 percent credible set does not include zero. The elasticities are standardized by the OLS estimate of the standard deviation of the relevant reduced-form residual; 10Y: 10-year Treasury yield; ΔP : personal consumption expenditure price deflator (first difference); ΔIP : manufacturing industrial production (first difference); ΔEmp : private nonfarm payroll employment (first difference); ΔPCE : personal consumption expenditure (first difference); SMR: excess stock market return; EBP: excess bond premium. See the text for details.

model that omits the EBP (center column), and in an identically specified model that omits the EBP and the excess stock market return (right column). Figures A.6 and A.7 in Appendix C display impulse responses of all remaining variables. The omission of the EBP from the baseline model leads to a smaller change of the response of industrial production. Instead, the omission of both the EBP and the excess stock market return results in an attenuation of the response of industrial production comparable with the one documented in section 4. Hence, the excess stock market return is also a relevant variable to characterize the effects of monetary policy.

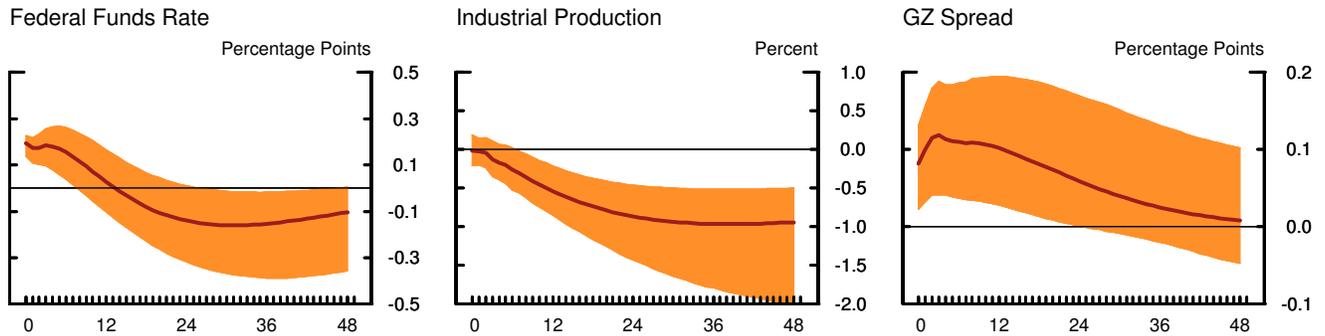
Figure 13 displays the fraction of forecast error variance in industrial production attributed to the monetary shock in the three models. Figures A.8 and A.9 in Appendix C display impulse responses of all remaining variables. Although the monetary shock identified in the full model explains up to 20 percent of movements in industrial production, the same shock explains only 8 percent in the model without the EBP and less than 5 percent in the model without the EBP and the excess stock market return.

Table 4 reports the contemporaneous elasticities of the fed funds rate to changes in all other variables in the system for the three variants of the Gilchrist-Zakrajšek SVAR model. To enhance comparability, the elasticities are standardized by the standard deviation of the VAR reduced-form residual of the relevant variable. The posterior distribution of all elasticities has substantial probability mass on both positive and negative values for all variables but the EBP and the excess stock market return. A 12 basis point increase in stock market returns leads to a 9 to 12 basis point monetary tightening. Note also that when the EBP is omitted from the proxy SVAR, the elasticity of the fed funds rate to stock market returns becomes larger and more significant. This result suggests that corporate bonds and stock prices might have both a common factor and idiosyncratic sources of variation that characterize the response of monetary policy. Finally, the estimated contemporaneous response of monetary policy to prices is not statistically significant.

Figure 14: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(ALTERNATIVE MEASURES OF CREDIT SPREAD)



(a) Trivariate Proxy SVAR with Baa Credit Spread



(b) Trivariate Proxy SVAR with Gilchrist and Zakrajsek (2012) Credit Spread

NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a one standard deviation monetary policy shock identified in a trivariate proxy SVAR. The response of industrial production has been accumulated. Shaded bands denote the 90 percent pointwise credible sets. See the text for additional details.

7 Alternative Measures of Credit Spreads

In the baseline specification, we followed Gertler and Karadi (2015) and used the EBP of Gilchrist and Zakrajsek (2012) as a measure of credit spreads. But as discussed in section 3.2, the EBP is the component of credit spreads related to the price of risk, and it excludes variation in spreads to changes in expected losses. To test whether our results are due to this unique feature of the EBP, we re-estimate the baseline trivariate model using two alternative measures of credit spreads.

Panel (a) of Figure 14 displays the impulse responses to a one standard deviation monetary shock when we replace the EBP with the spread between BAA corporate bonds and the 10-year Treasury yield described in section 3.2. Panel (b) of Figure 14 displays the impulse responses to a one standard deviation monetary shock when we replace the EBP with the full Gilchrist and Zakrajsek (2012) credit spread index.

The impulse responses are broadly in line with those reported for the trivariate proxy SVAR specification. A one standard deviation monetary policy shock elicits an initial 20 basis point increase in the fed funds

Table 5: ELASTICITY OF FEDERAL FUNDS RATE
(ALTERNATIVE CREDIT SPREAD MEASURES)

η_{EBP}	η_{Baa}	η_{GZS}
-0.1	-0.13	-0.11
[-0.24, -0.01]	[-0.32, -0.03]	[-0.29, -0.01]

NOTE: The table reports the median estimates of the elasticity of the federal funds rate to the EBP (η_{EBP}), the Baa - 10-year credit spread (η_{Baa}), and [Gilchrist and Zakrajsek \(2012\)](#) credit spread (η_{GZS}). The elasticities are standardized by the OLS estimate of the standard deviation of the relevant credit spread residual: $u_{EBP} = 0.2$, $u_{Baa} = 0.1$, and $u_{GZS} = 0.16$. 90% credible sets are reported in brackets. See the text for details.

rate, followed by a rapid decline and switch to a more accommodative—relative to its initial level—stance of policy. The response of both measures of credit spreads is hump-shaped and more persistent than the response of the EBP. The decline in industrial production is more pronounced than in the baseline model, peaking at negative 1 percent at about three years. The sharp and persistent decline in real activity might be reflected in a decline in expected corporate cash flows and hence an increase in expected losses. This component of corporate credit spreads is excluded from the EBP and might account for the different contour in the responses of credit spreads to monetary shocks.

Finally, Table 5 reports the contemporaneous elasticities of the fed funds rate to changes in three measures of corporate credit spreads. To enhance comparability, the elasticities are standardized by the standard deviation of the VAR reduced-form residual of the relevant credit spread measure. A one standard deviation increase in any measure of credit spreads—approximately 15 to 20 basis points—leads, all else being equal, to an immediate accommodation in the policy stance of about 10 basis points. The posterior distributions for the BAA and the [Gilchrist and Zakrajsek \(2012\)](#) spread have more mass on negative values, corroborating the idea that indeed monetary policy might react to both tightening in financial conditions and information about risk contained in credit spreads.

8 Conclusion

In this paper, we developed a framework for Bayesian inference in proxy SVARs and used it to examine a monetary SVAR in which identification of monetary shocks is achieved using proxies constructed from high frequency data. We find that, at least for the Great Moderation period, monetary policy both affects and endogenously reacts to asset prices. Compared with conventional estimates—which often ignore the endogenous response of monetary policy to credit spreads—monetary policy shocks have a more prominent role in business cycle fluctuations and explain about 20 percent of movements in industrial production and in corporate spreads.

There are several avenues for future research. First, the importance of monetary shocks documented in this paper is larger than in typical New Keynesian dynamic stochastic general equilibrium (DSGE) models. One possibility is that the models used in this paper might still be missing some variables that are key to characterizing the endogeneity of monetary policy and might have important effects on inference. Another possibility is to confront DSGE models with the evidence presented in this paper, which could be informative about the specification and estimation of nominal, real, and financial rigidities, as well as about the specification of the monetary policy rule.

Second, financial variables could potentially interact with other macroeconomic policies. For example, using Ramey's (2011) measure of government spending shocks, Barro and Redlick (2011) find that an increase in government spending reduces corporate spreads. This suggests that typical fiscal SVARs which omit financial variables might be subject to the same bias documented in this paper.

Finally, our Bayesian framework, by jointly modeling and estimating the SVAR and its relationship with the proxy, opens up the possibility to integrate proxy identification with standard identification strategies. Potential applications include the refinement of the identification of coefficients or impulse responses for which available proxies are uninformative—as, for instance, the systematic response of monetary policy to prices documented in this paper—as well as the identification of structural shocks for which proxies are not available.

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Appendices

A Bayesian Estimation

In this section, we first present the posterior sampler. We then describe the hyperparameters for the sampler used in the estimation of the models presented in the paper. Finally, we derive the closed-form description of the conditional likelihood of the proxy given the VAR data.

A.1 The Posterior Sampler

The posterior distribution of the proxy SVAR is

$$p(\Phi, \Sigma, \Omega, \beta, \sigma_\nu | Y_{1:T}, M_{1:T}) \propto p(Y_{1:T}, M_{1:T} | \Phi, \Sigma, \Omega, \beta, \sigma_\nu) p(\Phi, \Sigma, \Omega, \beta, \sigma_\nu), \quad (19)$$

where the first term on the right hand side is the likelihood function already discussed in Equation (13) and

Algorithm 1 (Block Metropolis-Hastings) *At iteration i*

1. Draw $\Sigma, \Phi | Y_{1:T}, M_{1:T}, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}$.

For Σ We use a mixture proposal distribution (suppressing dependence on parameters for notational convenience),

$$q(\Sigma | \Sigma_i) = \gamma p(\Sigma | Y_{1:T}) + (1 - \gamma) \mathcal{IW}(\Sigma; \Sigma_i, d),$$

where $p(\Sigma | Y_{1:T})$ is the known posterior distribution of Σ under $Y_{1:T}$ and $\mathcal{IW}(\cdot; \Sigma_i, d)$ is an Inverse Wishart distribution with mean Σ_i and d degrees of freedom. For Φ we use the known distribution $p(\Phi | Y_{1:T}, \Sigma)$ as a proposal in an independence MH step.

- Draw Σ^* according to $q(\Sigma | \Sigma_i)$.
- Draw Φ^* according to $p(\Phi | Y_{1:T}, \Sigma^*)$.
- With probability α , set $\Phi^i = \Phi^*$ and $\Sigma^i = \Sigma^*$, otherwise set $\Phi^i = \Phi^{i-1}$ and $\Sigma^i = \Sigma^{i-1}$. The probability α is defined as

$$\alpha = \min \left\{ \frac{p(M_{1:T}, Y_{1:T} | \Phi^*, \Sigma^*, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}) p(\Sigma^*)}{p(M_{1:T}, Y_{1:T} | \Phi^{i-1}, \Sigma^{i-1}, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}) p(\Sigma^{i-1})} \frac{q(\Sigma^{i-1} | \Sigma^*)}{q(\Sigma^* | \Sigma^{i-1})}, 1 \right\} \quad (20)$$

2. Draw $\Omega | Y_{1:T}, M_t, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}$.

Use an Independence Metropolis-Hastings sampler using the Haar measure on the space of orthogonal matrices.

- Draw Ω^* from the Haar measure by using Theorem 9 in [Rubio-Ramírez, Waggoner, and Zha \(2010\)](#).
- With probability α , set $\Omega^i = \Omega^*$, otherwise $\Omega^i = \Omega^{i-1}$. The probability α is defined as

$$\alpha = \min \left\{ \frac{p(M_{1:T}|Y_{1:T}, \Phi^i, \Sigma^i, \Omega^*, \beta^{i-1}, \sigma_\nu^{i-1})}{p(M_{1:T}|Y_{1:T}, \Phi^i, \Sigma^i, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1})}, 1 \right\} \quad (21)$$

3. Draw $\beta, \sigma_\nu | Y_{1:T}, M_t, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}$.

Use a random walk Metropolis-Hastings step for each proposal

A few words on the design of the sampler. In Step 1, when $\gamma = 1$, the proposal density form (Φ, Σ) is $p(\Phi, \Sigma | Y_{1:T}) = p(\Sigma | Y_{1:T})p(\Phi | Y_{1:T}, \Sigma)$, the posterior distribution of the reduced form coefficients conditional on the data $Y_{1:T}$. When using the Minnesota prior, this posterior distribution is known in closed-form, making the algorithm computationally efficient. But to the extent that the proxy is informative about the reduced form residuals u_t , the posterior of the reduced form parameters $p(\Phi, \Sigma | Y_{1:T}, M_{1:T})$ might be very different from the posterior $p(\Phi, \Sigma | Y_{1:T})$, in which case using $p(\Phi, \Sigma | Y_{1:T})$ as a proposal is not a good idea. To deal with this situation we use a mixture proposal for Σ that adds a the random walk-like component $IW(\cdot; \Sigma^i, d)$.

Obviously, some care must be taken in setting both γ and d . A good rule of thumb is to start with $\gamma = 1$. If the acceptance rate is too low, lower γ and fine-tune the size of the random walk step through the hyperparameter d . Even though this algorithm worked well in the applications presented in this paper, this sampler is not likely to be efficient when the posterior of $p(\Phi, \Sigma | Y_{1:T}, M_{1:T})$ is very different from the posterior under only the VAR data, $p(\Phi, \Sigma | Y_{1:T})$. In this case, alternative samplers could be used, potentially operating directly on the structural parameters (A_0, A_+) . Candidates simulators include those in [Bognanni and Herbst \(2014\)](#), who use Sequential Monte Carlo methods to elicit SVAR posteriors, and [Waggoner, Wu, and Zha \(2014\)](#), who construct a striated Metropolis-Hastings algorithm. For the models considered here, a sampler based on the one in [Bognanni and Herbst \(2014\)](#) produced the same posterior estimates.

A.2 Sampling Hyperparameters

Sampler in Section 4.1. For our baseline estimation, We set $\gamma = 1$, as the similarity of $p(\Phi, \Sigma | Y_{1:T})$ and $p(\Phi, \Sigma | Y_{1:T}, M_{1:T})$ is quite high. When capping the measurement error with $\bar{\sigma}_\nu = 0.5$ or $\bar{\sigma}_\nu = 0.25$, we set $\gamma = 0.8$ and $d = 5$, to ensure a better exploration of the parameter space. We estimating the larger models in Section 6, we shrink the Minnesota prior with $\lambda_2 = 3$. All the results reported in the paper are based on 50,000 draws from the posterior distribution of the structural parameters with a burn-in period of 10,000 draws.

A.3 The conditional density $p(M|Y, \Phi, \Sigma, \Omega, \beta, \sigma_\nu)$

Let Σ_{tr} be the lower Cholesky of Σ . For an t th observation, we have

$$\begin{bmatrix} y_t - \Phi x_t \\ m_t \end{bmatrix} = \begin{bmatrix} \Sigma_{tr}\Omega & O \\ \mathbf{b} & \sigma_\nu \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \nu_t \end{bmatrix} \quad (\text{A-1})$$

$$\text{where } \mathbf{b} = [\beta, 0, \dots, 0]. \quad (\text{A-2})$$

This implies that the joint distribution of $u_t (= y_t - \Phi x_t)$ and m_t is normally distributed, mean zero, with a variance matrix given by:

$$V = \begin{bmatrix} \Sigma & \Sigma_{tr}\Omega\mathbf{b}' \\ \mathbf{b}\Omega'\Sigma'_{tr} & \mathbf{b}\mathbf{b}' + \sigma_\nu^2 \end{bmatrix}$$

This means that m_t given u_t is also normal.

$$M_t|Y_t, \Phi, \Sigma, \Omega, \beta, \sigma_\nu \sim N(\mu_{M|Y}, V_{M|Y})$$

The conditional mean is given by

$$\mu_{M|Y} = \mathbf{b}\Omega'\Sigma'_{tr}\Sigma^{-1}u_t \quad (\text{A-3})$$

$$= \mathbf{b}\Omega'\Sigma_{tr}^{-1}u_t \quad (\text{A-4})$$

$$= \beta\Omega'_{.1}\Sigma_{tr}^{-1}u_t \quad (\text{A-5})$$

The second equality follows from $\Sigma_{tr}\Sigma'_{tr}\Sigma^{-1} = I$ and the third equality follows from the definition of \mathbf{b} . The conditional variance is given by,

$$V_{M|Y} = \mathbf{b}\mathbf{b}' + \sigma_\nu^2 - \mathbf{b}\Omega'\Sigma'_{tr}\Sigma^{-1}\Sigma_{tr}\Omega\mathbf{b}' \quad (\text{A-6})$$

$$= \sigma_\nu^2 \quad (\text{A-7})$$

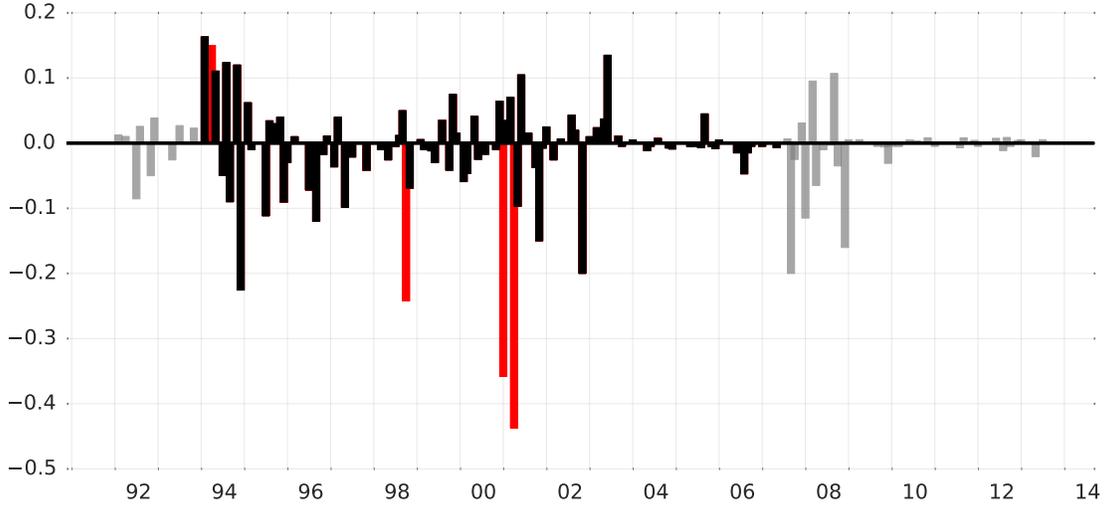
B Endogeneity of Surprises from Intermeeting Announcements

Between 1994 and 2007:6, the FOMC has made 108 announcements associated with regularly-scheduled FOMC meetings, and four announcements associated with intermeeting interest rate moves. Figure A-1 plots the monthly series of unexpected policy changes. The black bars show the aggregated shock series associated with regularly-scheduled meetings for our baseline sample 1994:1-2007:6, with the pre- and post-sample series shown in grey bars. The four intermeeting moves, highlighted in red-dashed bars in Figure A-1, occurred on April 18, 1994; October, 15, 1998; January 3, 2001; and April 18, 2001. The April 1994 interest rate increase is the second-largest increase in our sample, and the three other meetings represent the three largest cuts. While these four policy actions were unannounced and consequently largely unexpected, they were taken in response to economic conditions, and particular attention was paid to developments in financial markets. We report below four excerpts from the Minutes (first episode) and the Statements associated with these episodes.

- **April 18, 1994.** Policy change: 25 basis points increase. Unexpected change: 15 basis points increase. *In financial markets, sharp declines in bond and stock prices suggested that speculative excesses had been reduced, and ongoing portfolio realignments probably were shifting long-term financial assets to firmer hands.*
- **October 15, 1998.** Policy change: 25 basis points cut. Unexpected change: 23 basis points cut. *Growing caution by lenders and unsettled conditions in financial markets more generally are likely to be restraining aggregate demand in the future.*
- **January 3, 2001.** Policy change: 50 basis points cut. Unexpected change: 40 basis points cut. *These actions were taken in light of further weakening of sales and production, and in the context of lower consumer confidence, tight conditions in some segments of financial markets, and high energy prices sapping household and business purchasing power.*
- **April 18, 2001.** Policy change: 50 basis points cut. Unexpected change: 43 basis points cut. *Capital investment has continued to soften and the persistent erosion in current and expected profitability, in combination with rising uncertainty about the business outlook, seems poised to dampen capital spending going forward. This potential restraint, together with the possible effects of earlier reductions in equity wealth on consumption and the risk of slower growth abroad, threatens to keep the pace of economic activity unacceptably weak.*

One striking common feature that sets these episodes apart from the regularly scheduled meetings is that the surprise component is nearly identical to the policy change. The reason is that, as these policy actions were unscheduled, markets did not set up in advance of the policy rate decision. Consequently, the fed funds

Figure A-1: Unexpected Changes to the Target Federal Funds Rate



NOTE: Sample period: monthly data from 1990:M1 to 2012:M12. The bars depict unexpected movements in the target federal funds rate. The red-dashed bars indicate intermeeting policy moves.

futures immediately prior to the announcements do not reflect market expectations about the policy change.³²

Motivated by the anecdotal evidence presented above, we formally investigate whether the inclusion of intermeeting policy moves in our shock series leads to endogeneity. To this end, we estimate a battery of univariate regressions:

$$\epsilon_t^{MP} = \beta_0 + \sum_{i=1}^T \beta_i^x x_{t-i} + \nu_t,$$

where x is in turn the *EBP*, the monthly growth rate of IP, the stock market return, the nominal federal funds rate, a measure of term spread, and a measure of real interest rate.³³ We set ϵ_t^{MP} to either m_t^{RM} , which denotes unexpected policy changes announced at regularly-scheduled FOMC meetings, or to $m_t^{RM} + m_t^I$, where m_t^I denotes intermeeting policy moves. We choose T using the Akaike information criterion.

We report in Table A-1 the sum of coefficients expressed in basis points, as well as the F-statistic of the null where each coefficient equals zero. According to the first row of Table A-1, m_t^{RM} cannot be predicted by any variable but the 2-year real interest rate. The addition of m_t^I makes the proxy predictable by all variables but the stock market returns. A high *EBP* predicts some of the unexpected cuts in the target rate, and a strong economy predicts some of the unexpected increases in the target rate. These effects are consistent with

³²van Dijk, Lumsdaine, and van der Wel (2014) provides supportive evidence for this thesis.

³³The term spread is defined as the difference between the returns on a 10 year and 3 month U.S. Treasury bond.

Table A-1: PREDICTABILITY OF MONETARY POLICY SHOCKS

Predictor	EBP	ΔIP	LMRET	FFR	TS
m_t^{RM}	-0.31 [0.18]	0.30 [0.30]	0.00 [0.99]	-0.21 [1.70]	0.18 [1.72]
$m_t^{RM} + m_t^I$	-2.75 [4.82***]	1.83 [5.12**]	-0.01 [2.56*]	-0.46 [5.73***]	0.87 [1.50]

NOTE: The dependent variable in each specification is ϵ_t^{MP} , a measure of monetary policy shocks. ϵ_t^{MP} equals either m_t^{RM} , which denotes unexpected policy changes announced at regularly-scheduled FOMC meetings, or $m_t^{RM} + m_t^I$, where m_t^I denotes intermeeting policy moves. LMRET = value-weighted total stock market (log) return; TS = 3m/10y term spread. For each regression we report the sum of coefficients $\sum_{i=1}^T \beta_i^x$, where the lag length T is chosen using the Akaike information criterion. We report in bracket the F-statistic of the null where each coefficient β equals zero. The F-statistic is based on HAC standard errors. * $p < .10$, ** $p < .05$, and *** $p < .01$.

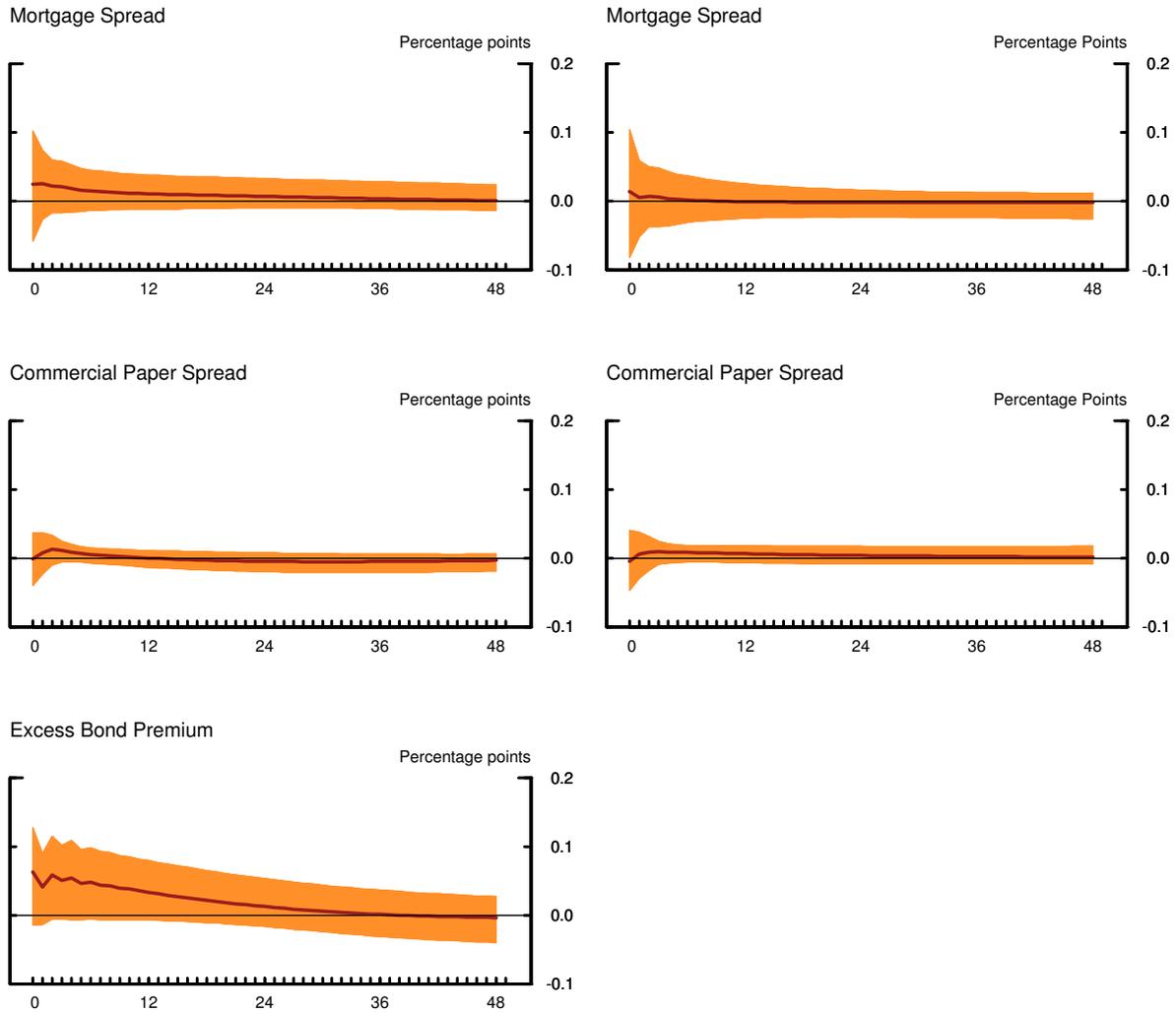
the narrative from the FOMC Minutes and Statements reported above. Moreover, past values of the nominal fed funds rate predict the proxy because all four moves were taken to accelerate an ongoing tightening (first episode) or loosening (last three episodes) of the policy stance.³⁴

While it is true that the Proxy SVAR is valid even when the proxy is correlated with *previous* nonmonetary shocks, this kind of predictability, together with anecdotal evidence above, is suggestive of a more pernicious contemporaneous correlation, which is not directly testable. Consistent with this evidence, we find that the use of a proxy that includes both scheduled and unscheduled meetings in the estimation of the BP-SVAR (not reported) induces a bias towards zero in the effects of monetary policy shocks on both credit spreads and real activity. Moreover, [Romer and Romer \(2004\)](#) also exclude these unscheduled meetings in the construction of their narrative-based shock series, as there is no corresponding Greenbook forecast with which to purge the systematic component from these changes.

³⁴[Miranda-Agrippino \(2015\)](#) provides a more detailed analysis on similarly constructed proxies and also finds that the inclusion of unscheduled policy decisions leads to predictability of the proxy.

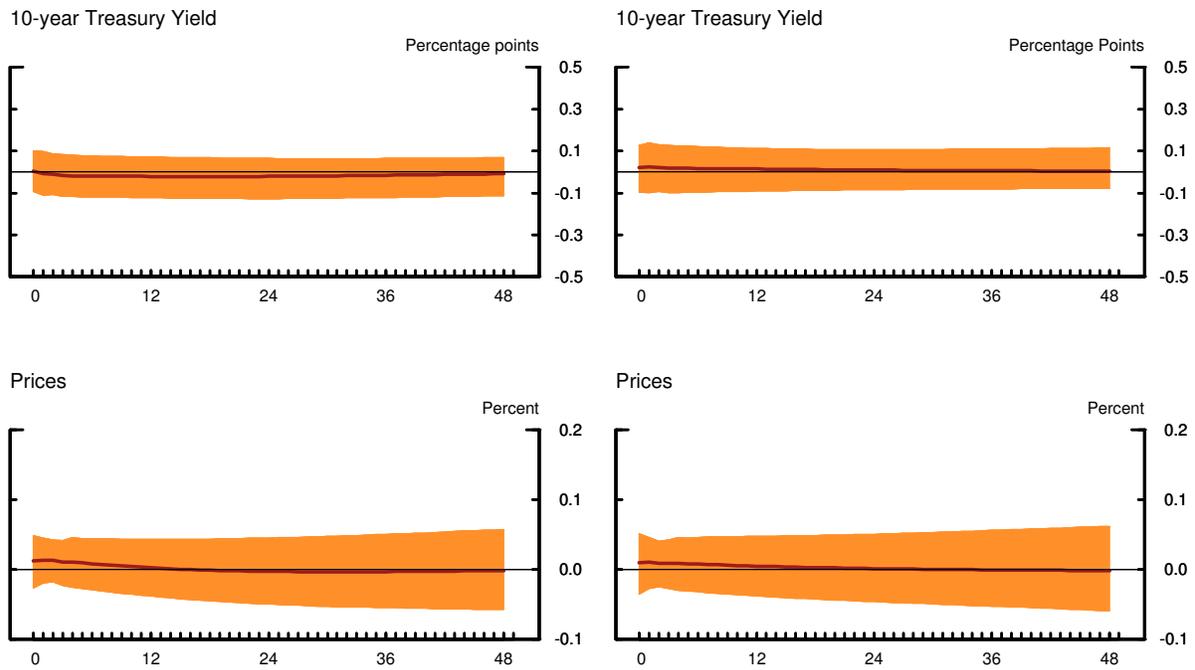
C Additional Figures and Tables

Figure A.2: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
(SELECTED VARIABLES FROM THE [GERTLER AND KARADI \(2015\)](#) VAR MODEL)



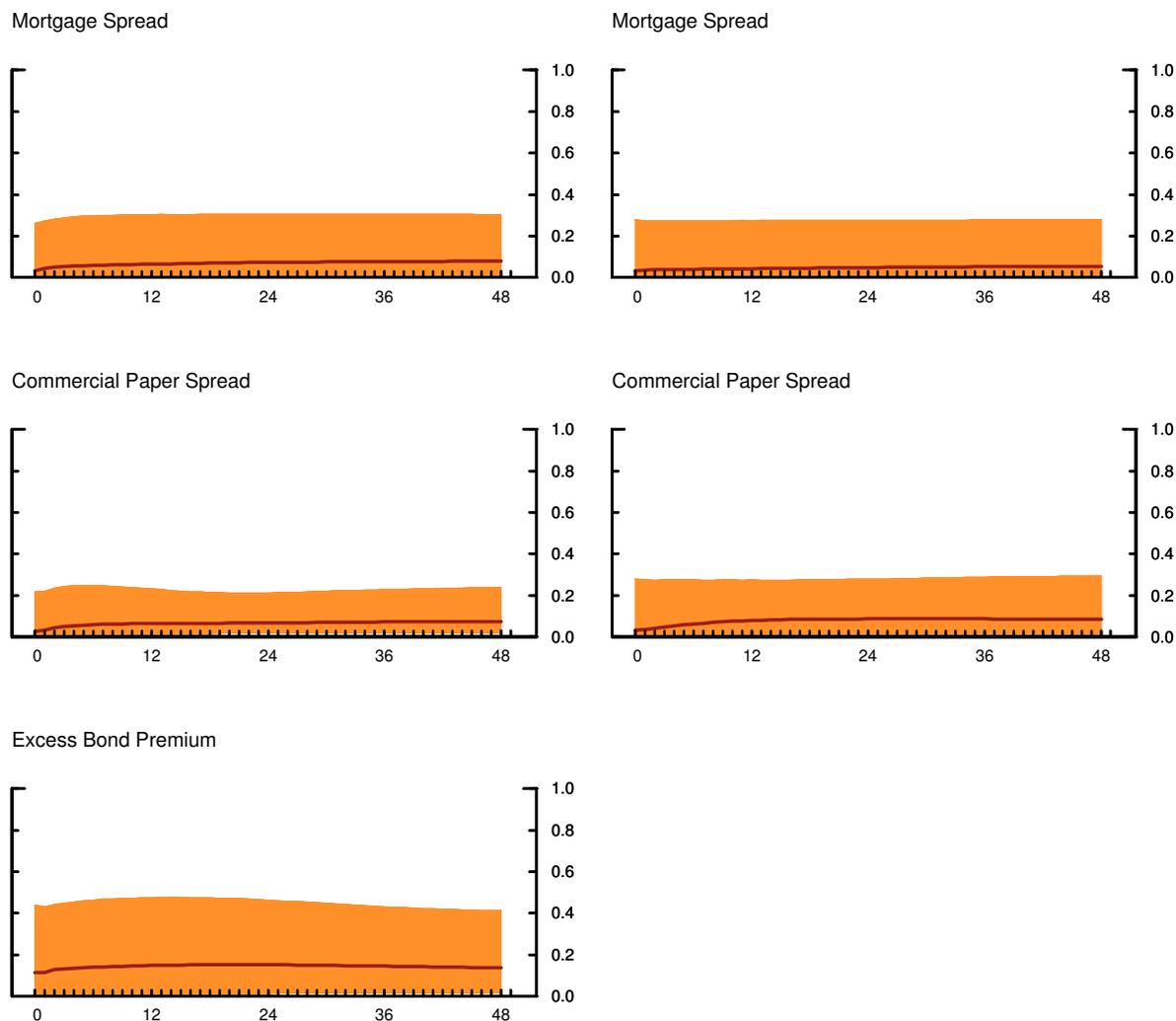
NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation monetary policy shock identified in the [Gertler and Karadi \(2015\)](#) VAR model (left column) and in the same model without the EBP (right column). Shaded bands denote the 90 percent pointwise credible sets.

Figure A.3: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
 (SELECTED VARIABLES FROM THE [GERTLER AND KARADI \(2015\)](#) VAR MODEL)



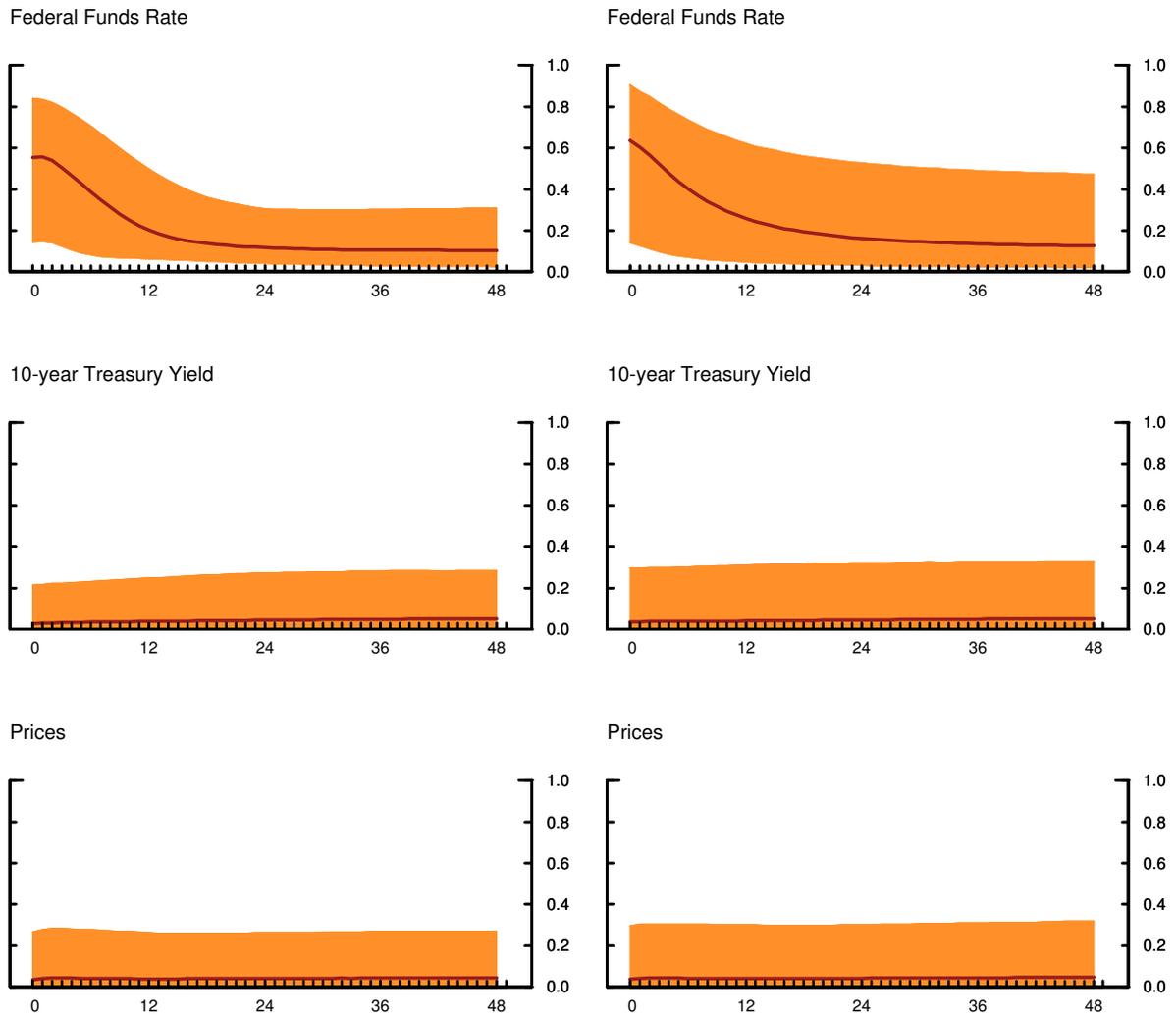
NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation monetary policy shock identified in the [Gertler and Karadi \(2015\)](#) VAR model (left column) and in the same model without the EBP (right column). The response of prices has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

Figure A.4: FORECAST ERROR VARIANCE DECOMPOSITION OF MONETARY POLICY SHOCKS
 (SELECTED VARIABLES FROM THE [GERTLER AND KARADI \(2015\)](#) VAR MODEL)



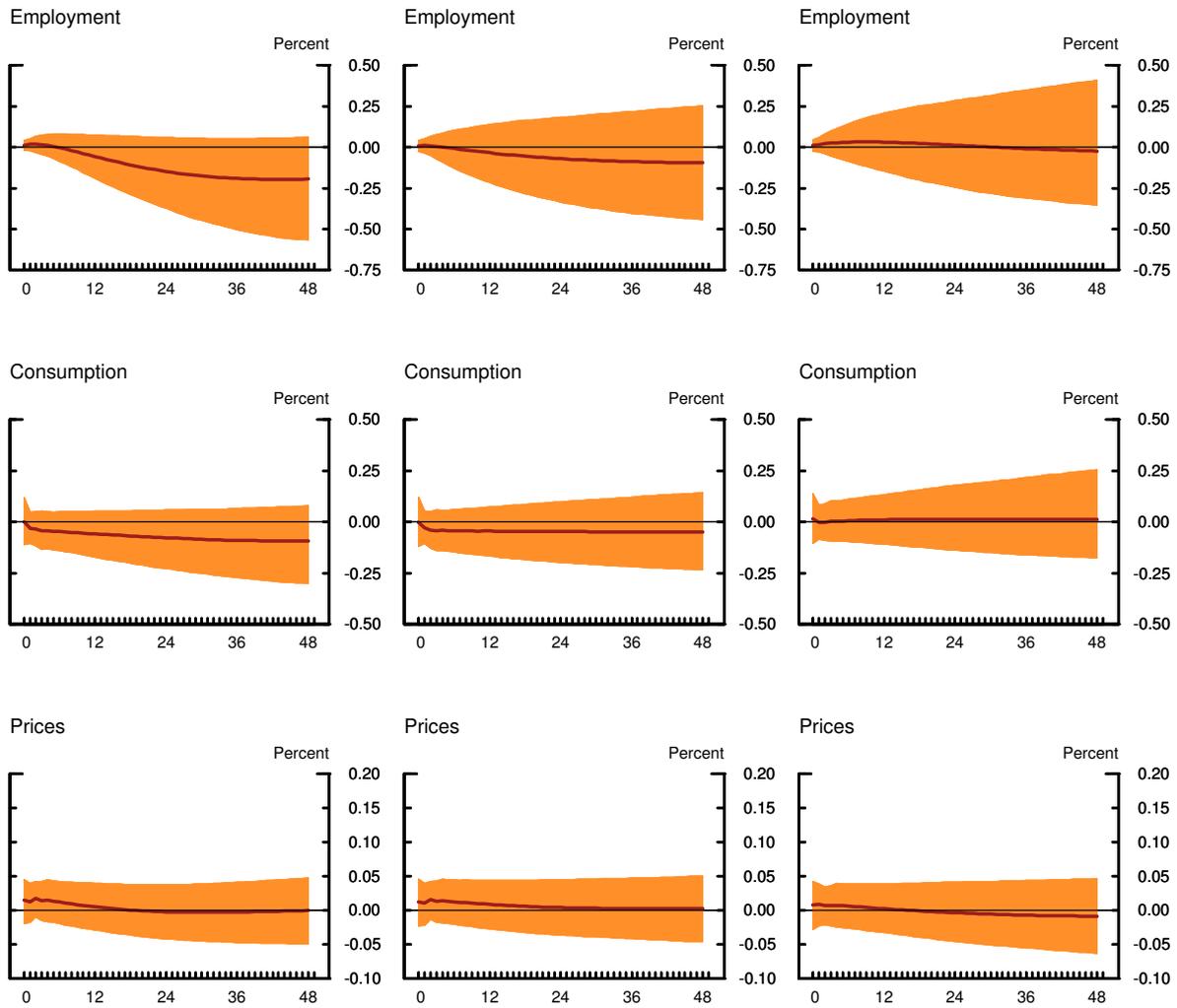
NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a 1 standard deviation monetary policy shock identified in the [Gertler and Karadi \(2015\)](#) VAR model (left column) and in the same model without the EBP (right column). Shaded bands denote the 90 percent pointwise credible sets.

Figure A.5: FORECAST ERROR VARIANCE DECOMPOSITION OF MONETARY POLICY SHOCKS
 (GERTLER AND KARADI (2015) VAR MODEL)



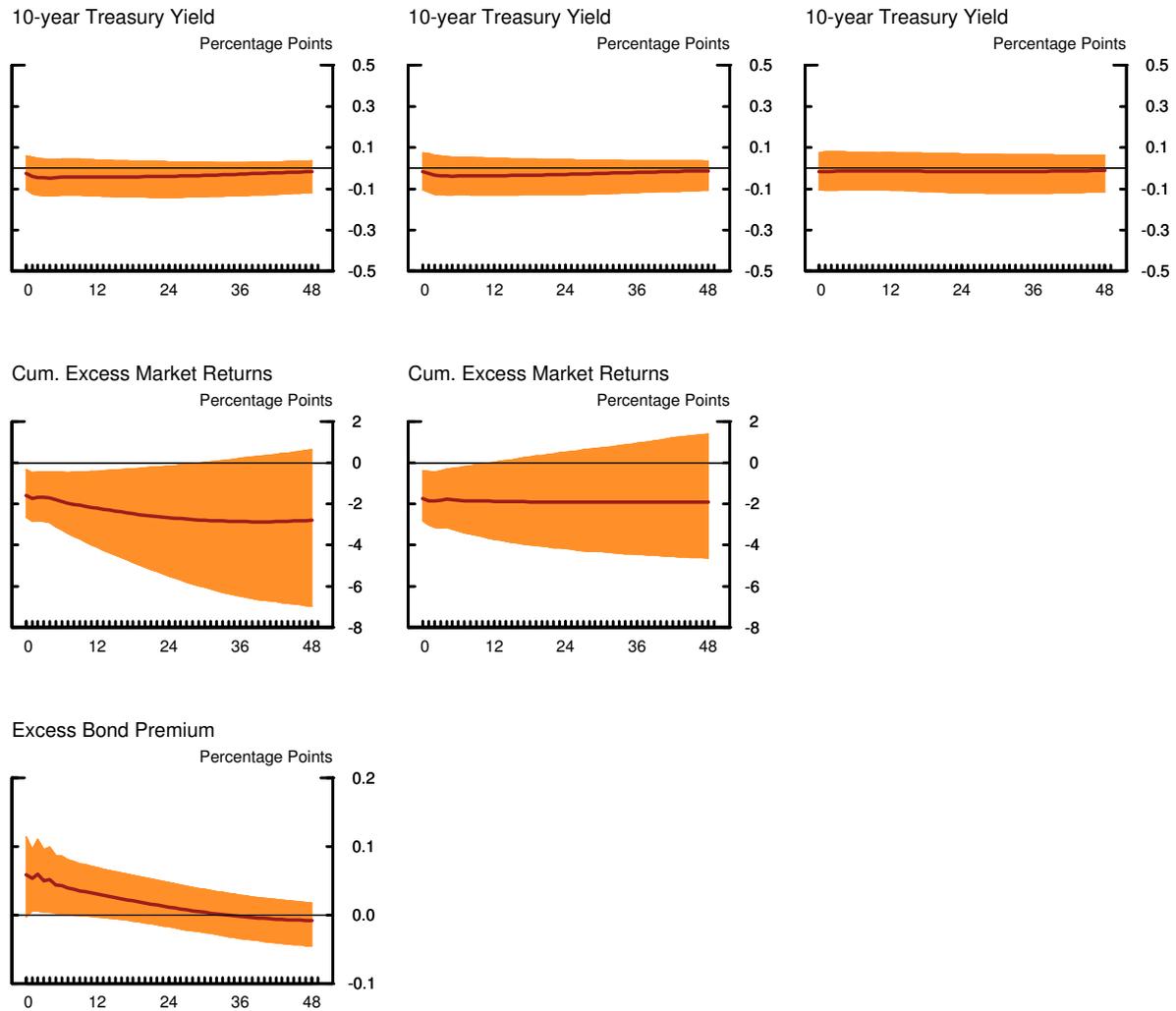
NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a 1 standard deviation monetary policy shock identified in the [Gertler and Karadi \(2015\)](#) VAR model (left column) and in the same model without the EBP (right column). The forecast error variance decomposition of prices is based on the level of the variable. Shaded bands denote the 90 percent pointwise credible sets.

Figure A.6: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
 (SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



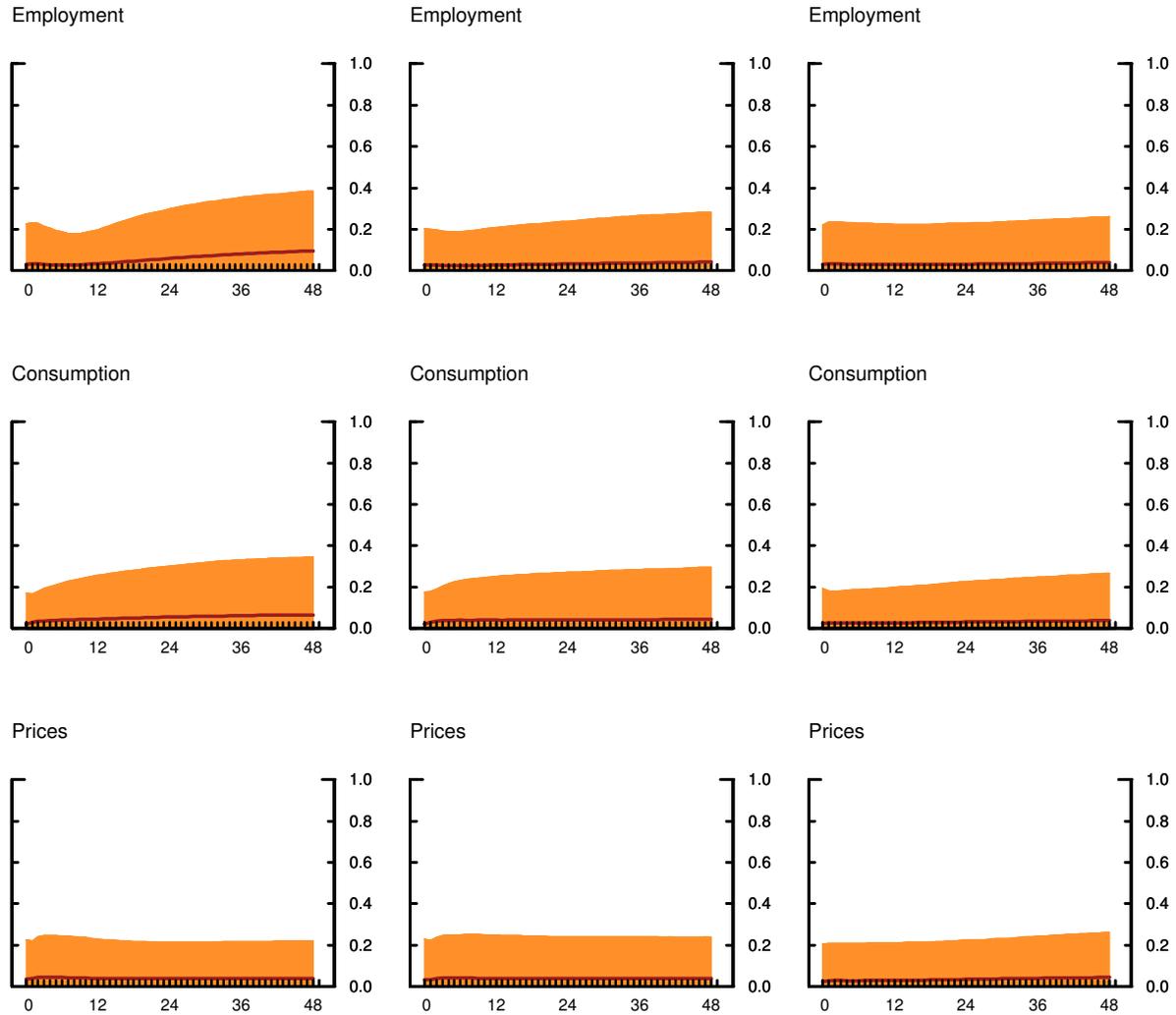
NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without both the EBP and the excess stock market return. The responses of consumption, employment and prices have been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

Figure A.7: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK
 (SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



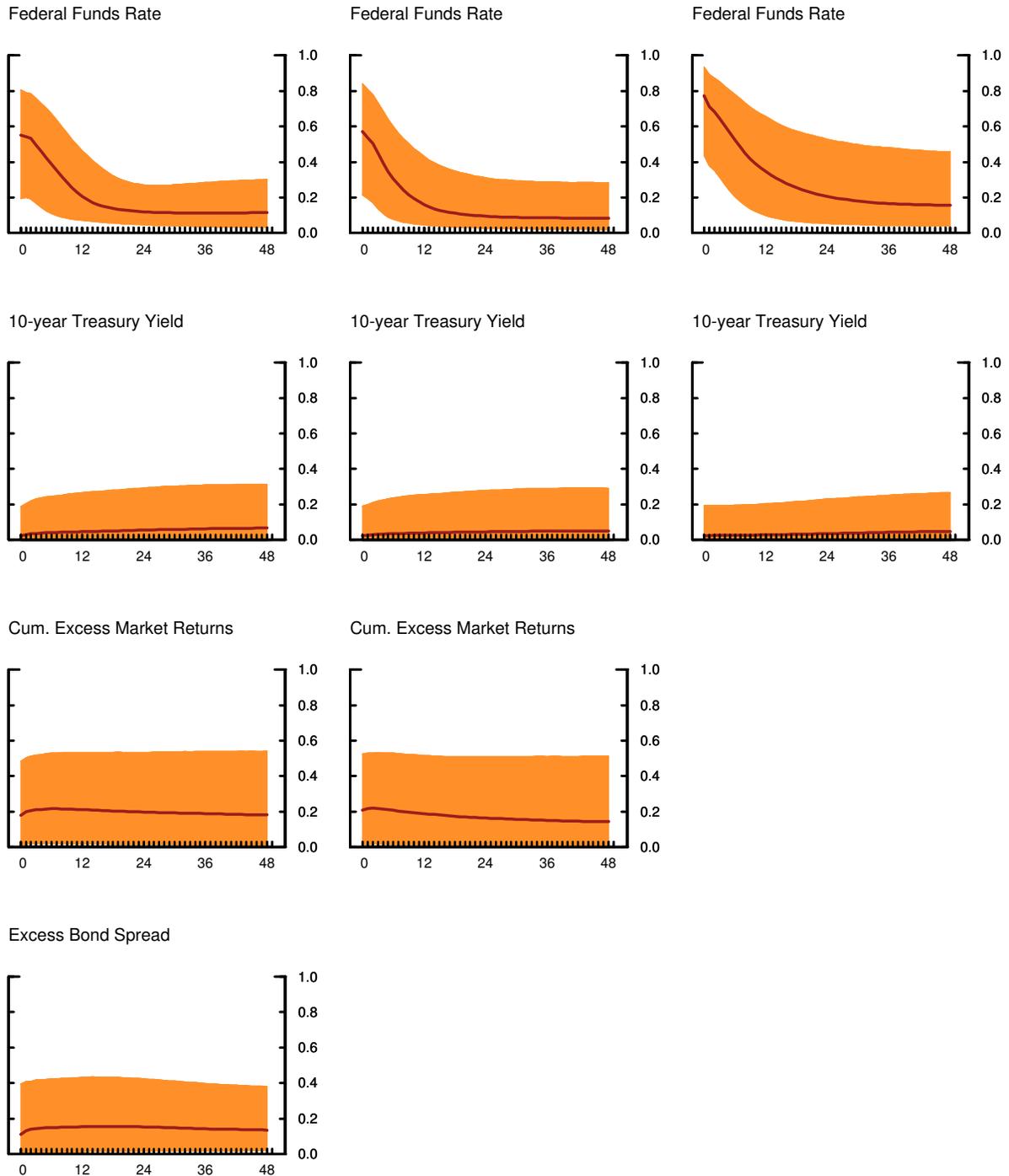
NOTE: The solid line in each panel depicts the median impulse response of the specified variable to a 1 standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without both the EBP and the excess stock market return. The responses of the excess market return has been accumulated. Shaded bands denote the 90 percent pointwise credible sets.

Figure A.8: FORECAST ERROR VARIANCE DECOMPOSITION OF MONETARY POLICY SHOCKS
 (SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a one standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without both the EBP and the excess stock market return. The forecast error variance decomposition of consumption, employment, and prices is based on the level of the variable. Shaded bands denote the 90 percent pointwise credible sets.

Figure A.9: FORECAST ERROR VARIANCE DECOMPOSITION OF MONETARY POLICY SHOCKS
(SELECTED VARIABLES FROM THE GILCHRIST-ZAKRAJŠEK VAR MODEL)



NOTE: The solid line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a one standard deviation monetary policy shock identified in the Gilchrist-Zakrajšek VAR model (left column), in the same model without the EBP (center column), and without both the EBP and the excess stock market return. The forecast error variance decomposition of the excess market return is based on the level of the variable. Shaded bands denote the 90 percent pointwise credible sets.